Essays on consumer portfolio choice and credit risk

Tingting Ji

The Ohio State University

30. October 2004

ESSAYS ON CONSUMER PORTFOLIO AND CREDIT RISK

Dissertation

Present in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

Tingting Ji, M.A.

The Ohio State University

2004

Dissertation Committee:

Paul Evans, Adviser

Lucia Dunn

Pok-sang Lam

Approved by

____

Adviser

Economics Graduate Program

ABSTRACT

Three essays comprise this dissertation. The first essay uses panel data to show that labor income risk alone cannot explain limited stock market participation. However, transaction costs and household demographics, considered jointly, can determine both the discrete choice of whether to hold stock and the amount held, conditional on whether the household is already investing in the stock market. Transaction costs are proxied by state-level number of brokers per capita.

The second essay builds on the first essay. I measure two different covariance terms. One is between self-evaluated house value and uninsurable labor income risk. The other is between housing investment return and stock return. The results show that homeownership has a diversification effect on stock holdings. This effect occurs because adding a house to the household portfolio can significantly decrease the overall risk of the portfolio.

The last essay empirically shows that unemployment is significant in determining both consumer bankruptcy filings and delinquency even after controlling for household demographics. Furthermore, I show that unemployment and the debt/wealth ratio also affect the choice of whether to file for bankruptcy under chapter 7 or chapter 13, after controlling for demographics. The paper then points out some of the implications the empirical results have for policy-makers and banking regulators.

Dedicated to my parents

ACKNOWLEDGMENTS

I thank my adviser, Paul Evans for intellectual support, encouragement and patience, which made this thesis possible. I also thank him for devoting lots of time to correct many errors in the paper. In the past several years, I have learned so much from him and really help me to grow both personally and professionally.

I thank Lucia Dunn and Pok-sang Lam for their patience, stimulating discussion and help.

I also thank Qing Liu, Xianghong Li, Pat Reagan and Qingyan Shang, who helped me at various stages of the paper.

My thanks also go to my parents and my brother, who have given me great support my whole life.

VITA

May.6, 1975 ....Born - Tianjin, P.R.C

1999...M.A. The Ohio State University

1998...B.A. Nankai University, P.R.C

FIELD OF STUDY

Empirical Econometrics

Finance

Consumer Credit Risk

TABLE OF CONTENTS

LIST OF TABLES

Page

CHAPTER 1

1.1 Introduction

In recent years, the problem of household portfolio choice has received increasing attention in financial economics, spurred mostly by the mystery of why so few American families held stocks even though the equity premium was very attractive. The data show that the average risk premium over the post-war period is over nine percent. During the more recent period of 1980 to 1994, which is the sample period in my paper, the risk premium is still as high as almost eight percent (see table 1 for details). The risky asset I use to calculate the risk premium is the monthly value-weighted return on the Standard & Poor's Composite Index, which is defined as return(t)/return(t-1)-1. The yearly value-weighted return can be easily calculated from this monthly return, through the formula 1+R=(1+r(1))*(1+r(2))*…(1+r(12)). In this formula, r(1),…,r(12) are the monthly returns from January to December. The risk-free asset return I use is 30-day bill returns, and the yearly return is calculated using the same method as for risky returns.

However, in spite of the high risk premium, most American households still choose NOT to hold stocks. The previous literature has shown that most households hold remarkably simple portfolios—basically, checking and savings accounts[1] and a house.

Bertaut & Starr-McCluer (2000) show that over half of all American households do not hold any type of stock investment.

This phenomenon obviously contradicts traditional portfolio choice theory. Following the theories in Merton (1969, 1971) and Samuelson (1969), with complete markets, if investors are living off financial income generated from multiple financial assets, all investors should invest in risky assets. If the investment opportunities are constant and investors have isoelastic expected utility, the models also predict that all investors should invest in equities in the same proportion. Only the level of holdings will differ across investors due to their different amounts of wealth. However, this scenario breaks down whenever the market becomes incomplete. Market incompleteness comes from many sources, like short sale constraints, market frictions, or non-marketable incomes. When markets are incomplete, investors cannot price and capitalize future state-contingent income. Among these causes of incompleteness, economists give the most attention to labor income risk, since it is perhaps the most obvious risky, uninsurable background risk. Investors (or, workers, in the labor market) and employers can only negotiate contracts on a period-by-period basis, due to the moral hazard and adverse selection problem (Viceira (2002)). As a result, investors cannot write enforceable claims against future labor income. When investors become uncertain about future labor income flows, they prefer to hold less risky and more liquid assets as a hedge against labor income changes, especially during economic downturns.

A number of researchers have been exploring this issue both theoretically and empirically. For example, Gakidis (1998) investigated this problem by introducing shocks to both labor income process itself and to its growth rate and confirmed that labor income risk does indeed have a major effect on asset accumulation when households have borrowing constraints. Gakidis also tried to reconcile this with “buffer stock” saving behavior. Chakraborty and Kazarosian (1999) also point out that both permanent and temporary earnings shocks can generate a precautionary savings motive. Angerer(2003) used NLSY79 data to show that income risk significantly reduce share of risky assets in an investor’s portfolio.

This problem becomes more complicated when risky labor income interacts with risky financial asset returns. Pratt and Zeckhauser (1987) were the first to point out that bearing one risk may make investors less willing to take another risk, even when the two risks are statistically independent. Kimball (1993) developed the notion of “standard risk aversion” and its implication for optimal investment. He states that “standard risk aversion is necessary for any loss-aggravating risk to reduce the optimal level of investment in any other independent risk.” Viceira (2001) has also explicitly documented that when labor income risk is idiosyncratic, investors should hold more risky assets when they are employed than when they retire. If there is a negative correlation between income risk and stock return risk, holding stocks is a kind of hedge against income variations. But if the correlation is positive, stocks will not be that favorable. Vissing-Jørgensen (2000) investigated the nonparticipation mystery in the stock market and the considerable heterogeneity of different households, finding that positive mean non-financial income affects the probability of holding stock and the risky shares conditional on being a stockholder.

However, very few papers have documented the magnitude of the effects of risky labor income on the probability of holding stock. Some work has shown the statistical significance of risky, uninsurable labor income in financial decisions. Angerer(2003) used random effect Tobit model to estimate the significantly negative effect of permanent income shocks on risky share holding relative to liquid assets and net wealth. Vissing-J∅rgenson (2001) shows that increasing the conditional mean of real nonfinancial income by $10,000 (in 1982-1984 dollars) can increase the probability of holding stock by 3.4 percent, a significant but small effect. However, it is more natural to consider the change in probability of holding stock when the moments of real labor income change by one standard deviation. Souleles (2001) is the first to challenge the effect of labor income risk on portfolio choice. He points out that labor income risk is not enough to capture the total background risk the household faces. The commonly used standard deviation of income change cannot fully summarize the riskiness in the household income process, including illness, divorce or going to college. However, Souleles did not estimate the magnitude of the effect of risky, uninsurable labor income on household portfolio choice.

In this paper, I use Heckman's sample selection model to measure the magnitude of the effect of risky labor income on household portfolio choice. I find that the moments of labor income can significantly affect household decisions about whether to hold stock and how much to hold. However, their effect on the probability of holding stock is not as large as one might expect.

In contrast, transaction costs turn out to be important in determining stock holding behavior. Previous literature has identified the importance of transaction costs in portfolio choice. Souleles (2001) shows that over 85% of respondents in the CEX sample do not make any securities transactions over the 12-month reference period. This suggests that transaction cost is important. He also used an ordered probit model to show that it is optimal for the household to incur transaction costs and purchase or sell securities only when the holding level falls below or above a desired level, i.e., households follow a state-dependent (S, s) rule. Vissing-J∅rgensen (2001) used structural state dependence in analyzing the Panel Study of Income Dynamics to show the existence of an entry cost, a fixed transaction cost, and a proportional transaction cost. He also estimated the per-period participation cost to be around $200 per household.

Few studies have actually estimated the impact of transaction cost on stock holdings, mostly due to the difficulty of capturing transaction cost in the econometric analysis. For the first time in the literature, I argue that the number of securities brokers per capita in a particular state can reflect transaction costs. Even though this does not quantify the actual amount of transaction costs a household faces, it is a good proxy. I show that households do dramatically increase their probability of holding stock and the amount they hold when there are more brokers per capita.

Additionally, this paper extends the previous literature in the sense that it employs a longitudinal panel of randomly selected US households over a 15-year period. Previous work on this topic has been mostly performed using cross-sectional survey data, which cannot fully reveal what happens in a household over time. Longitudinal panels can correct this deficiency. In this paper, I use data from the Panel Study of Income Dynamics (PSID), including three waves of PSID wealth supplements, to investigate the effects of the moments of labor income and brokers per capita on household portfolio choice. The PSID has yearly observations of labor income, permitting estimation of their labor income dynamics. Furthermore, there are observations of wealth components at five-year intervals. Even though there are fewer time-series observations on asset holdings, overall household behavior in entering and leaving the equity market can be clearly seen, and my assumptions about the effects of income and transaction costs can also be checked.

The paper also has some important macroeconomic implications. First, stock investment shapes aggregate wealth investment, which is recognized as a critical issue in analyzing the effects of government fiscal policies. Second, individual investment behavior can also reflect market efficiency (Shiller (1997)). Third, understanding household investment preferences can help in constructing retirement funds and Social Security. Especially in the presence of transaction costs, economists argue that investing Social Security funds in equities can help low-income households participate in the stock market (Abel (2000)).

Due to the limitations of the available data, this paper considers only two kinds of assets: risky stocks and risk-free checking and savings accounts. The rest of the paper will be divided into four parts. The first section describes the model for estimating expected labor income, income risk and the correlation between income growth rate and stock return. The second part describes the data set used and the construction of the sample. The third part is the econometric analysis of a Heckman two-stage model with and without including brokers per capita. The last section concludes.

1.2 The Model

1.2.1 Model for expected labor income and income risk

Household earnings innovation was first investigated in Hall and Mishkin (1982). They decomposed income changes into permanent and transitory movements and investigated the stochastic relationship of consumption to income. The new method for modeling income uncertainty for a typical household is demonstrated by Carroll (1992), where actual income is equal to permanent income multiplied by a transitory shock, $Y_t = P_t \varepsilon_t$, and the permanent income grows by a fixed factor, G, i.e. $P_t = GP_{t-1}$. Carroll used those methods to investigate household consumption and savings behavior. Carroll and Samwick (1997) extended this analysis by introducing variance of shocks to both permanent and transitory income, showing that wealth is principally held to insulate consumption from income uncertainties.

More recently, interest in these income models has resurfaced as a result of interest in investigating the effect of income shocks on the stockholding puzzle. In my paper, to estimate the moments of labor income, I use the following method from Carroll and Samwick (1997)[1]:

$$\ln w_{it} = p_{it} + \varepsilon_{it}$$
$$p_{it} = g_{it} + p_{it-1} + \eta_{it}$$

In each period t, a household i with a set of characteristic variables receives labor income w_{it}. In the decomposition of the logarithm of wage income, $\boldsymbol{p_{it}}$ is the permanent component, which is defined as the amount of log labor income the household receives in the absence of any transitory income shocks. In each period, the permanent component grows by a factor *g*. η_{it} is a shock to permanent income and ε_{it} is a transitory shock to the logarithm of labor income. It is assumed that both permanent and transitory shocks are normally distributed, i.e. $\varepsilon_{it} \overset{iid}{\sim} N(0,\sigma_{\varepsilon i}{}^2)$, $\eta_{it} \overset{iid}{\sim} N(0,\sigma_{\eta i}{}^2)$[1]. I further assume that g_{it} can be predicted linearly with a vector of household demographics at time $t-1: X_{it-1}$. So, we can have

$$\ln w_{it} = \ln w_{it-1} + g_{it} + \eta_{it} + \varepsilon_{it} - \varepsilon_{it-1} \tag{1}$$

From this equation, I calculate the conditional mean and variance of log labor income:

$$E(\ln w_{it} \mid \ln w_{it-1}, x_{it-1}) = \ln w_{it-1} + g_{it}$$
$$V(\ln w_{it} \mid \ln w_{it-1}, x_{it-1}) = \sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2$$

The normality of the two error terms then implies that:

$$E(w_{it} \mid w_{it-1}, x_{it-1}) = w_{it-1} e^{g_{it}} e^{\frac{1}{2}(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)}$$
$$V(w_{it} \mid w_{it-1}, x_{it-1}) = (w_{it-1} e^{g_{it}})^2 e^{(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)} (e^{(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)} - 1)$$

So to calculate above moments, we need the terms $\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2$.

The general procedure[2] in the previous literature is to regress $(\ln w_{it} - \ln w_{it-1})$ on a set of observable and exogenous households characteristics $\boldsymbol{X_{it-1}}$ in each year. The

---

[1] This model was also employed in Viceira(01) and Vissing-J∅rgensen(00).

[2] See also Vissing-J∅rgensen(00) and Angerer (03)

predicted values will be estimates of g_{it}, the residuals will be estimates of $\eta_{it} + \varepsilon_{it} - \varepsilon_{it-1}$, and the sample variance of the residuals will be estimates of $\sigma_{\eta i}{}^{2} + 2\sigma_{\varepsilon i}{}^{2}$.

However, the above methodology is applicable if and only if the household *i* earns positive labor income in all of the sample years, which contradicts reality. In each time period, the household may experience a "good state" when it receives a positive amount of labor income, but there is still a probability π_i that the household will not earn any wage income. A careful examination of the PSID sample shows that about 15-20 percent of each year's sample receives no labor income.

The conventional method to solve this problem is to add one dollar to the zero income cases, which enables their income to be logged. However, I argue that this method biases the estimated mean and standard deviation of the income process, since the underlying processes governing positive income flow and zero income flow are totally different.

In the "good state," the evolution of log labor income can be governed by the summation of a permanent component and a transitory component, where the permanent component can be predicted linearly from a vector of household demographics such as age, education, occupation, race, etc. This is the standard human capital model. In the "bad state," the household does not receive any wage income, perhaps due to temporary unemployment, illness, and divorce or school attendance. Even though the probability of such "bad states" is relatively small, it can indeed have an important impact on behavior. The determinant of household behavior in light of such unexpected events will be the likelihood of a "bad state," and the empirical estimation of labor income should account for events leading to a "bad state" (Gakidis (1998)). The need for a separate process for dealing with zero-income cases becomes even clearer when Gakidis (1998) uses PSID data to plot the distribution of ($\ln w_{it} - \ln w_{it-1}$), which has fat tails on both sides, where both tails are associated with entry into or exit from unemployment (or any other events leading to zero wage rate).

Therefore, the commonly used measure, standard deviation of income changes from OLS regression, cannot adequately summarize the risks the household actually faces. Statistically, this method can bias the results, too. For example, a household with positive labor income in all sample years will have an income process whose innovations have a smaller standard deviation but greater persistence. Another household with zero labor income in only one or two of the sample years will have an income process whose innovations have a large standard deviation but less persistence. A household might invest more in risky assets under the first income process than under the second (Souleles (2001); Storesletten, Telmer and Yaron (1997); Constantinides and Duffie (1996)). However, if we treat the two households equally under the same income process as in the above model, the model predicts that the second household holds more equities. The econometric reason behind this is that the sample residuals from the OLS regression will have a large standard deviation for the second household, and this large variance term enters exponentially in the estimated expected labor income, so the second household is expected to have a large labor income and thus hold more risky assets than the first household. Further, this bias may be fairly large, because around 20% of the sample has zero labor income in at least one year, and almost all of these households have sizeable incomes in other years. This large proportion of zero income years will lead to an unreasonably high level of expected income and income risks. A careful examination of this method shows that it may estimate that about 150 households in the sample are millionaires when they actually earn only $30,000-$50,000 a year. Obviously this could significantly bias the econometric analysis. However, there is no reason to drop these families since one can econometrically account for any unexpected events, such as divorce, illness, and temporary layoff, which prevent the household from earning any labor income.

To resolve the zero-income episodes, we can consider the problem as a sample selection issue as described in Heckman (1979). In this selection process, a household with a zero income event is included if and only if the household can earn positive wage income. Moreover, because the regression in equation (1) actually involves the selection of both w_{it} and w_{it-1}, this is actually a bivariate sample selection issue. To address this problem, I first run a bivariate probit model to estimate the probability of earning positive income in both years t and t-1 for each household and then calculate their inverse mills ratios by using the bivariate cumulative distribution function and bivariate probability density function. Then I pool all households in all of the sample years and estimate the log difference of labor income using a random effect model, with the variables from the standard human capital model as independent variables, together with the two inverse mills ratios calculated from the bivariate probit model to adjust for sample selection.

The bivariate probit model is also based on the following standard human capital model.

$$\ln w_{it} = g_{it-1} + \varepsilon_{it}$$
$$\ln w_{it-1} = g_{it-2} + \varepsilon_{it-1}$$

Where both ε_{it} and ε_{it-1} are distributed as N(0, 1). However, $\ln w_{it}$ or $\ln w_{it-1}$ can only be observed when w_{it} or w_{it-1} is positive. So I create the two discrete variables D_{it} and D_{it-1}, which are defined as

D_{it}=1 iff $\ln w_{it}$>0 and 0 otherwise

D_{it-1}=1 iff $\ln w_{it-1}$>0 and 0 otherwise

In this equation, D_{it} is the indicator variable for whether the household earns positive labor income in a particular year. So what I estimate is actually the following:

$$D_{it} = \beta_1' X_{it-1} + \varepsilon_{it}$$
$$D_{it-1} = \beta_2' X_{it-2} + \varepsilon_{it-1}$$

where X_{it-1} and X_{it-2} are vectors of household characteristics at time t-1 and time t-2 respectively. Maximum likelihood method is used to estimate the bivariate probit model and obtain the following four probabilities:

$$P(\ln w_{it} > 0, \ln w_{it-1} > 0)$$
$$P(\ln w_{it} > 0, \ln w_{it-1} = 0)$$
$$P(\ln w_{it} = 0, \ln w_{it-1} > 0)$$
$$P(\ln w_{it-1} = 0, \ln w_{it-1} = 0)$$

Obviously, we can calculate the four inverse mills ratios by using the bivariate cumulative distribution function and bivariate probability density function. Then, depending on whether $\ln w_{it}$ and $\ln w_{it-1}$ are positive or zero, each household is assigned different inverse mills ratios.

The predicted values and residuals can be easily obtained for these households from the above random effect estimation. Finally, I use the predicted values and sample variance of residuals to estimate the conditional expected income and income risks.

1.2.2 Model for the covariance between labor income growth and stock return

Viceira (2001) shows that a small, positive correlation between labor income risk and stock return risk significantly reduce the optimal investment in equities, because of their inability to hedge against unexpected labor income innovations. This is consistent with Kimball (1993)'s notion of "standard risk aversion," which implies that a loss-aggravating background risk will reduce the optimal investment in another risky asset. However, Vissing-J∅rgensen (2000) finds no evidence of this hedging effect when investigating the interaction term for the correlation coefficient and expected nonfinancial income.

In this paper, I estimate the covariance of labor income growth with stock returns by summing the products of the difference of log labor income and stock returns across all sample years. For each family, I estimate $\text{cov}(\Delta \ln w_{it}, R_t)$ by $\sum_t \Delta \ln w_{it} \bullet R_t$, where $\Delta \ln w_{it} = \ln w_{it} - \ln w_{it-1}$ and R_t is the value-weighted gross return with dividend reinvestment for the S&P500. Note that for those families with zero labor income, I add $1 so they have zero log labor income, since doing this will not change the results.

I also estimate the conditional covariance by using $\sum_t (\Delta \ln w_{it} - g_{it-1}) \cdot R_t$, but the term g_{it} has a negligible effect on the covariance. This finding is unsurprising given that the demographic variables in X_{it-1} are unlikely to be apparently correlated with subsequent returns in the stock market and vice versa.

1.3 Data

In this paper, I use five different data sets. The Panel Study of Income Dynamics (PSID) is the main data set for income dynamics, family demographics and portfolio choice. The S&P500 provides the representative yearly return and the covariance of income growth rate and stock return. Both Census data and the Bureau of Labor Statistics' survey of securities brokers are used to calculate the number of brokers per capita. Finally, I use state-level per capita income from the Bureau of Economic Analysis (BEA) to check whether the effect of brokers per capita is merely a proxy for per capita income. The data sets are described as follows.

1.3.1 PSID (Panel Study of Income Dynamics) Data

Because the model for labor income involves looking at the dynamics of labor income of the same household over a number of years, the Panel Study of Income Dynamics (PSID) is a natural choice. The PSID is a large, longitudinal, representative study of US households. The survey randomly sampled about 6000 American families in 1968 and has tracked income and other family characteristics for both the original main families and the split off families since that time. The PSID data files provide a wide variety of information about both families and individuals collected over the span of the study. The central focus of the data is economic and demographic, with substantial detail on income sources and amounts, employment, family composition changes, and residential location. But its content is much broader than this: in 1984, the PSID introduced a supplement with questions on family wealth, such as the value of checking and savings accounts, stockholding, credit card debt, and total wealth. This wealth supplement has been administered every five years since 1984. Therefore, analyzing the portfolio choice decisions of those households should give a good picture of wealth holding among US households.

For my sample, I use data for 1979-1996. I drop the Latino over-sample in 1990-1992. I then use 1979 as my base year, treating all families in this year as main families, and subsequent split off families are dropped from the sample. A family is also dropped if it did not respond in any year. Finally, I drop the two cases in which total asset income of other family members is top-coded. This leaves a balanced panel of 4884 households.

Since stockholding behavior is recorded at the household level, I construct the total labor income for each household in each year. This is calculated as labor income of head + labor income of spouse + taxable income of other family members – asset income of other family members. Since asset income of other family members is bracketed in 1980-1982, I broke down the same variable in 1983, using the cutoff levels for 1980-1982, and then calculated the mean value within each bracket, substituting this as the true value in 1980-1982. Even though the 1994-1996 income data are finalized, one cannot identify asset income for family members other than the head and spouse. Therefore, the asset income for other family members in 1993 was subtracted from total taxable income to get an approximation for labor income. I also tried another method, simply taking taxable income as labor income since very few other family members actually have asset income, but the two approaches generate virtually identical results. If (taxable income – asset income) was negative in 1980-1982, I set the difference to zero.

I deflate total household labor income by the annual average of the CPI-U to get real labor income. The vector of observable household characteristics, X_{it-1}, includes the age of household head and its square along with dummy variables indicating whether the head has a college degree or more, whether the head is a white-collar worker and whether the head is white. All of these demographic variables are widely used proxies for human capital, which is strongly related to labor income. I also include a dummy variable for the employment status of the head in the bivariate probit step, since this can be a crucial determinant of whether the household has zero or positive income in a particular year. This variable is excluded from the regression for wage income, since it is not a factor considered in human capital by labor economists as a determinant of the labor income of those who earn positive labor income.

I then calculate the residuals for each family in each year, employing the bivariate probit model and three different yearly cross-sectional regressions as specified in the previous section, which is actually an estimate for $\eta_{it}+\varepsilon_{it}-\varepsilon_{it-1.}$ The sample variance of residuals for each family will be used for sigma. The fitted value for 1994 will be seen as an estimate of g_{it}. With those estimates in hand, we can calculate the expected mean and variance of labor income for each family.

1.3.2 Stock Return Data

To construct the sample covariance of labor income growth and stock return, I calculate $\sum \Delta \ln w_{it} * R_t$ for each family. R_t is the yearly gross return of the S&P500, and it is actually calculated from monthly value-weighted return with dividends, that is:

$$R_t = 1 + r_t = (1 + r(1)) \cdot (1 + r(2)) \cdot (1 + r(3)) \cdots\cdots (1 + r(12))$$

where $r(1) \cdots\cdot r(12)$ are monthly value weighted simple returns with reinvested dividends for the S&P500. Again, as is true for the moments for labor income, this estimate is created in the same way for 1984, 1989 and 1994.

1.3.3. Data for Brokers per Capita

It may be a difficult task to actually quantify transaction cost. Not only do we have no way to know what kind of securities the households are actually holding, it is also a formidable task to figure out how many times an investor makes transactions in a certain time period, and how much he paid to the brokers or e-trade companies, or even how much time he spent investigating the market and figuring out his optimal strategy. However, one measure that seems worth trying is the number of brokers per capita in the state in which the household resides. The PSID has a state code for each household in each year, and population size is available from the Bureau of the Census for all years. The total number of employees in security brokerages is also available at the state level from the Bureau of Labor Statistics, but only for 1996-1999. I calculated the average growth rate of brokers per capita for each state between 1996 and 1999 and extrapolated backward to estimate brokers per capita for each state for 1984, 1989 and 1994. In this way, each household in the PSID can be assigned a measure of “brokers per capita” in 1984, 1989 and 1994 respectively.

1.3.4 Data for per Capita Income

Yearly state-level per capita personal income can be obtained easily from the Bureau of Economic Analysis. Since the econometric analysis involves 1984, 1989 and 1994, I extract per capita income only for these three years and then assign it to each household using the state code in the PSID data.

1.4 Econometric Analysis

1.4.1 General Description

I first give an overview of family asset holdings during this 15-year period. The frequency table shows that most families have either checking or savings accounts. The percentage with such accounts is quite stable, about 70% of the whole sample during all three waves of the wealth survey, with a high of 75% in 1989 (see table 4 for detail). The mean value put into checking and savings accounts increased significantly, by about $5000 every five years.

Residential housing seems to be the most important investment for households. As shown in table 5, the ownership of housing is above 60%, and it increases to almost 70% in 1993. The median value of housing is far greater than any other investment; it increases steadily from almost $55,000 to $75,000 during the 15-year period.

The picture for stock ownership seems quite different. First, the percentage of respondents holding stock is much lower—about half of those with checking/savings accounts, even though it is increasing rapidly over time (refer to table 6 for details). The median dollar value of stocks held also increased rapidly in the sample period, nearly doubling between 1984 and 1989 and more than doubling from 1989 to 1994 (again, see table 4 for details).

A more interesting phenomenon is revealed by the survey data: the same families do not hold stocks in 1984, 1989 and 1994. Only 592 families hold stocks in all three waves of the wealth survey. Only 751 families hold stocks in both 1984 and 1989. This is one of the effects that cross-sectional data cannot reveal, and it gives us some evidence that holding stock may be related to transaction costs.

At first glance, it seems that stockholding is strongly connected with labor income, since in all years the mean value of labor income in households who hold stocks is about twice as large as in those who do not hold stocks. However, stocks are not held only by high-income households; the range of labor incomes for stockholders is about twice as wide as for non-stockholders. This observation leads us to investigate the magnitude of the effect of risky labor income on portfolio choice and what else can drive the household in and out of the stock market.

1.4.2. Results on the Effects of Labor Income

Since the decision to hold stock may differ from the decision about how much stock to hold if the family already has stock, I first use the probit model to examine the effects of labor income on the decision to hold stock, and then see how this effect changes if the moments of labor income are changed by one standard deviation. The Heckman sample selection method is then employed to see how labor income affects how much stock is held if the household chooses to hold stock at all. The same framework is also used to see how the results may change if transaction costs are incorporated in the model.

The probit model is of the general form:

$$\boldsymbol{S}_{it}^{*} = \alpha_1^{'}\boldsymbol{X}_{it} + \varepsilon_{it}$$
$$\boldsymbol{S}_{it} = \alpha_1^{'}\boldsymbol{X}_{it} + \varepsilon_{it}$$

where S_{it}^{*} is the amount of stock holding for household *i* in year *t*, and

$S_{it}=1$ iff $S_{it}*>0$ and

$S_{it}=0$ iff $S_{it}^{*}=<0$.

S_{it} is the dummy variable indicating whether the household holds stock. The vector of observable characteristics that determines it is the same as that which determines S_{it}^{*}.

Angerer (2003) used NLSY 79 cohort data to estimate the effect of uninsurable labor income on risky shares as a percentage of net wealth or liquid assets. The econometric model is a random effect Tobit model, the dependent variable is risky shares relative to either liquid assets or net wealth. The independent variables include income risks imputed from Current Population Survey (CPS) and human capital factors. She found significantly negative effect of permanent income shocks on risky share holding.

The Heckman two-stage model in this paper is estimated using the maximum likelihood method. In the probit analysis, the moments (mean and standard deviation) of household total labor income and the covariance of annual labor income growth rate and stock return enter as regressors. The previous literature (see Bernheim (1997)) showed that access to financial knowledge (in the form of high school financial curriculum mandates) could significantly influence adults' financial decision-making. I use a dummy variable for whether the household head works in a financial company to proxy for such information and to control for the household's access to financial knowledge. Additional regressors include dummy variables for whether the head is white and male; age of the household head; education dummies for whether the head has received any college or higher education; a dummy for whether the head is a white-collar worker; and two dummies for the industry in which the head works (either manufacturing or for other business and services). Finally I include a variable indicating how many children the household has.

The probit result for the probability of holding stocks in all three waves of the wealth supplement is shown in table 9. Most important, expected labor income seems to have a very negligible effect. For example, in all three years, the estimated coefficient is almost indistinguishable from zero, and it is even slightly negative in 1984. However, labor income innovations indeed crowd out stock holdings—the coefficient of standard deviation of labor income is significantly negative in all three years, and the absolute value of this coefficient also increases steadily over the 15-year period. It seems that the riskier the labor income, the less likely people are to hold stock.

Although previous empirical work was unable to detect a statistically significant effect in the covariance between labor income and stock return, the covariance functions as expected here. If labor income prospects are positively correlated with stock market performance (perhaps for those who work in buy.com), households tend to avoid holding stock. By contrast, those whose labor income is negatively correlated with the stock market are more likely to hold stock since it is good means of hedging labor income risk. (See Viceira (2001) for the theoretical background.) Again, in my model the covariance variable shows a slightly upward trend of decreasing the probability of holding stock.

Given the statistical significance of the coefficients, we are more interested in determining the magnitude of the effect. In other words, we would like to know what would be the change in probability of holding stocks if the labor income risk is changed by one standard deviation. This result is shown in table 10. Since we are focusing on the effects of risky labor income, I only report the results for the three moments of labor income. The change in probability is obtained by keeping all other regressors at sample mean, while changing only of the moments of labor income by one standard deviation from the sample mean. Similar to the probit result above, the effect of mean labor income is quite negligible; increasing labor income by one standard deviation never increases the probability of holding stock by more than one percent! Labor income risk seems to be more important; the probability decreases by 2.6 percent in 1984, 4.2 percent in 1989 and more than 7 percent in 1994. The hedging term can decrease the probability of holding stock around 2 percent if it is increased by one standard deviation from the sample mean. However, this percentage is obviously quite small compared to the role of income risk presented in the theoretical model.

The magnitude of income risk remains almost the same in the sample selection results shown in table 11. Increasing the mean labor income by one million can only increase stock holding around 3 cents in 1994 and 10 cents in 1989, and this effect is even slightly negative in 1984. The standard deviation of labor income has a much larger absolute value, but it is not significant either, as it is within one standard deviation from zero in 1994, and just above one standard deviation in 1984.

However, these results are quite reasonable considering the underlying economic reasoning. First, Heaton and Lucas (1997) used a decision-theoretical model to show that investors are not sensitive to the labor income risk even though this risk can indeed discourage stock investment. They explain this is because labor income has a "bottom line" bad result, other than the financial investment, which can dramatically decrease the "effective risk aversion". Second, the theory predicts that uninsurable background risk can depress stock holdings, since it can change household tolerance toward bearing additional stock market risk. However, the labor income risk cannot actually fully capture the undiversifiable background risk faced by the typical household. The background risk can come from a private business, owner-occupied housing, labor income, etc. Heaton and Lucas (1999) used the "Tax Model" to show that private business owners invest less in stocks. Gentry and Hubbard (1998) also showed that entrepreneurs save more than other people. Housing is similar to private business in the sense that it is illiquid and undiversified, but it can give additional consumption flow to the homeowner and thus provides a highly levered position which can decrease stock holding (Heaton and Lucas (2000); Flavin and Yamashita, (1998)). Finally, treating positive income flow and zero income flow equally can also significantly bias the econometric results. The data have shown that zero income episodes do not only come from unemployment or layoff but can also be generated by events like illness, going to college, divorce, or retirement. Those are obviously non-income events. So, as argued above, different data-generating processes should govern positive income and zero income episodes. Treating them equally in the empirical work can inflate the effects of labor income risk. It should come as no surprise that the above model does not show significant labor income effects after adjusting for bivariate sample selection bias.

Turning to the other control variables in the probit model, they show rather reasonable positive effects, as already been documented in the previous literature. The most obvious is the life-cycle effect. As the household head ages, the household has a higher probability of holding stock and it holds more stock. This contradicts the conventional wisdom suggesting that investors should hold more stocks when they work and shift toward bonds after retirement. However, recent literature (Davis and Mehra (2002)) points out that investors hold an optimal portfolio consists of both risky equities and risk-free securities. Human capital is the largest component of wealth and is a risky asset, since future labor income is uncertain. However, human capital decreases as the investor ages because his productivity energy and the skills that he can bring into the labor market decline near retirement. From this point of view, the investor should shift towards stocks near retirement in order to maintain balance between risky and risk-free assets.

Having a male household head also has a significantly positive effect on stock holding. Male-headed households have a 34 percent chance of holding stocks, and they held $54,000 more in stocks than their female counterparts in 1984. This figure increases to $70,000 in 1994. Agnew, Balduzzi and Sunden (2000) find some similar results: males invest 19.43% more than females in stock according to a panel data from a large 401(K) plan. This is also consistent with the results from Hinz, McCarthy and Turner (1997), Baijtelsmit and VanDerhei (1997), and Sunden and Surette (1998), who find that women are more conservative investors than men, controlling for other background demographics.

Households with the head working in financial companies have a significantly higher probability of holding stock, probably due to their exposure to financial principles and investment skills. Bernheim and Garrett (1997) show the importance of financial knowledge in investment decisions. They use household survey data to show that high school consumer/financial curriculum mandates can equip students with practical investment decision-making skills in their adult lives. Bernheim and Garrett (1996) also show that retirement education offered by employers strongly influences household financial behavior.

Households with a well-educated head (with at least a 4–year college degree) are also far more likely to hold stocks than other households. Hubbard, Skinner and Zeldes (1995) suggest that better-educated households face lower background risks. Bertaut and Starr-McCluer (2000) find similar supporting results.

For the other family demographics, the effects are quite consistent with expectations. Having a managerial or professional job can increase the probability of holding stocks by at least 32 percent. The amount held is about $47,000 to $79,000 more than that in households with manufacturing jobs, conditional on being a stockholder. Being white is another important determinant of stock ownership, its effect ranges from 71 percent to almost 80 percent. Finally, the total number of children the head has can decrease the probability of holding stock, perhaps due to the financial burden of raising kids. In the sample selection step, I exclude the variable "number of kids the head has" from the probit step for the identification concern. Presumably this variable can only be taken as a kind of "entry cost" to the equity market in the sense that it only affects the decision to enter the stock market, because the head has to consider the possibility that more children will put greater demands on family wealth. However, this variable will not affect how much stock is hold as long as the household is already a stockholder. Hurst, Luoh and Stafford (1998) also used a probit analysis to show that having children decreases stock ownership.

From the results above, it is apparent that labor income risk does indeed crowd out stock market participation, but the magnitude is not as large as anticipated. On the other hand, human capital factors like age, education, occupation, race and industry form a significant share of background risk and can jointly determine household investment behavior.

We are also looking for other explanations of the stock market nonparticipation puzzle. Previous research has shown that this may be due in part to the transaction/information cost. Vissing-J∅rgensen (1998) used a censored regression model with unobservable stochastic thresholds to get an estimate of per-period participation cost. The median for an average household is around $200. As identified by Vissing-J∅rgensen (1998), stock market participation costs are multi-dimensional, including an entry cost, a fixed transaction cost, a proportional transaction cost and a per-period participation cost. Most brokerage accounts and mutual funds require a minimum investment of $2,000 ($1,000 for IRAs) or $100 per month based on meeting the minimum requirement. In most cases, investors still need to pay a commission, fee or sales load each time they buy or sell a security. With Morgan Stanley Choice, for example, the fee can account for 2.5% of the total equity for investments under $99,999. With the development of online trading, the costs can be lower, but investors are still subject to a minimum commission of $35 per trade for total investments under 1000 shares. The actual transaction cost may be beyond what can be measured by dollars. It takes time for an investor to equip himself with some general financial knowledge, to learn investment terminology, and to obtain the skills to track the market and manage a portfolio. The investor is also supposed to spend more time checking the market, making trading decisions and filling in tax forms over the life of the investment. During the "windfall" period, the investor may also bear the psychological burden of an investment failure.

However, empirical study of transaction costs posts difficulties since it is difficult to derive a testable implication. In this paper, I try a different perspective—using the number of brokers per capita as a proxy for transaction costs to determine if it has significantly negative results on stockholding. The econometric results are shown in the next section.

1.4.3 Results on the Effects of Transaction Costs

Guiso, Sapienza and Zingales (2002) find strong evidence that local financial development has an important impact on the economic success of the area and the individual household's behavior. The implication for the stock market is that regional financial developments grant households easier access to the stock market by decreasing transaction costs, especially information costs. The difficulty is to present support for the link between financial market development and stock market participation, showing the mechanisms through which this link operates. In this paper, I show that local brokers per capita is a sound indicator of the development of financial intermediation services, and this variable reflect the level of transaction costs faced by individuals and thus help explain stock market participation.

Econometrically, I use state-level brokers per capita in the sample selection model to show that increasing brokers per capita can significantly increase both the probability of entering stock market and the amount held conditional on being a stockholder.

In order to easily compare this model with the results for risky labor income, I estimate the same probit model again with brokers per capita as an additional regressor in all three years (1984, 1989 and 1994). The new results are shown in table 12. If we compare table 9 and table 12, we can see that the parameter estimates for other regressors remain almost the same as before, and that results for brokers per capita are quite significant in both 1984 and 1994. In 1984, having one more broker per 1000 in population increased the probability of holding stock by 3.5 percent. In 1994, this effect increases to 5.5 percent. The exception is 1989, when the parameter estimate shows a positive effect that is within one standard deviation from zero.

I then calculate the change in the probability of holding stock if brokers per capita increase by one standard deviation across the 50 states. Details are shown in table 13. Participation in the stock market increases by 0.7 percent in 1984, 0.2 percent in 1989 and almost 22 percent in 1994. The availability of brokers does appear to play a more important role than income risk in determining whether households hold stocks.

Finally, we are ready to repeat the sample selection regression with brokers per capita as an additional variable. Table 14 shows the new regression results. Similar to the results above, the parameter estimates for the income risk variables and other household demographics remain almost the same as in table 11. In 1984, increasing the number of brokers per capita by one per 1000 in population increases stockholding by $2,812, conditional on the household already having stocks in hand. The effect of one more broker increases to $3,933 in 1989. In 1994, the effect becomes much larger, as one more broker per 1000 in population leads investors to put around $13,000 more in the stock market.

There are four reasons for the positive effects of state-level brokers per capita. First, most security dealers can provide trained professional consultation services to investors. Brokers can work with investors on an individual basis to develop investment strategies suited to their individual needs. Most brokers also have comprehensive educational websites or brochures to help investors understand financial accounts, trading strategies and the economic situation. All of these can significantly decrease the costs of entering the stock market. Second, with the development of new trading methods, the investor can also trade online, by telephone or through the financial consultant. The brokers can also provide timely fundamental research information on equities; investment options and earnings estimate changes. They can also provide weekly market analysis based on unusual fundamental changes or investment developments. These can help investors to decrease the time they would otherwise invest in collecting this information and working out the investment strategy. Third, the spread of discount brokerage services provided by security dealers, plus the development of online trading, creates more competition among different brokers and can decrease the monetary costs of stock trading. Finally, the growth of brokers advertising and more investment opportunities give investors more chances and topics to discuss with each other and also with friends or coworkers who have not participated in the stock market yet. This can accelerate information exchange and decrease the costs of learning about investments. Furthermore, as more investors enter the stock market, the marginal cost of information acquisition for new investors will decrease. This can in turn attract more brokers. So the development of stock market investment will be self-reinforcing through the intermediation of brokers.

However, Guiso, Sapienza and Zingales (2002) also show that more financially developed regions have higher per capita GDP growth. One suspicion about the effect of brokers per capita is that it might be a proxy for higher state-level per capita income. If this is the case, then more active household stock market participation is not due to the number of brokers depressing transaction costs, but because the state has higher income on average. To check the robustness of my results, I therefore added state-level per capita income in both the probit and the sample selection step, to investigate whether per capita income affects the brokers per capita variable. The results, reported in tables 15 and 16, clearly show that this is not the case. We can see that per capita income does not play a consistent role over the 15-year period. In some years, it is not significant or even has a negative sign. More important, with the inclusion of per capita income, every other regressor, including number of brokers per capita, still remains at the same significance level.

As I remarked earlier, brokers per capita is by no means a perfect measure for transaction cost. It cannot incorporate proportional transaction costs like the bid-ask spread. Nor can I track what kind of securities the household was holding and the times at which they made transactions. However, we do know whether the household was holding stock at the time of the interview, and we know the dollar amount of stock holdings once every five years. In order to learn more about how transaction costs may have influenced stockholding behavior, I split the sample into different groups according to the amount of stock held and then examined how the households moved among the different groups in each of the five-year periods. The assumption here is if transaction costs, especially proportional costs, are appreciable, then the probability of staying in the same group or in the adjacent groups will be quite large; the probability of jumping from the bottom group to the top group and vice versa will be quite small. Also, if there exist unavoidable high entry costs, the likelihood of leaving the market will be quite small while that of staying outside will remain large.

1.4.4 Supplemental Results—Markov Chain Analysis

Since transaction costs discourage trading, households will either choose not to enter the market or incur the costs infrequently by trading less if they are already in the market. Souleles (2001) uses a probit model to show that household rebalancing motives are generated by a (S, s)-type dynamic whenever there are sizeable transaction costs. Hurst, Luoh and Stafford (1998) uses PSID data to show that stock market exits exceed entries over the period 1984-1994, suggests that capital gains cannot recover transaction costs.

A simple testable implication for my paper is to estimate a Markov chain for the probability of transferring across different states (state 0: outside the stock market and state 1: inside the market) during a certain time interval (five years in my sample). However, we can divide state one into more sub-states according to the amount of stocks held and investigate the probability of moving among these different states as well.

For the five-year periods 1984-1989 and 1989-1994, I categorized all households that did not have any stock in the initial year as group zero. The remaining households are equally divided into four groups, with the amount of stockholding increasing from group 1 to 4. Entries in the cells of the transition matrix, as in table 17 and table 19, are the percentage of households in the sample who moved across different groups. For example, the number 0.6677 in the 0-0 cell in table 17 means 66.77% of the sample held no stocks in either 1984 or 1989. Similarly, the number 0.0096 in the 2-3 cell means 0.96% of the sample was in group 2 in 1984 but moved up to group 3 in 1989. The last rows in table 17 and table 19 show the percentage of all of the households who were in the different groups in 1984 and 1989 respectively. Statistically, the probability of moving from group a in 1984 to group b in 1989 should be estimated as the number of people who moved divided by the total number of people who were in group a in 1984. Statistically, this is also the maximum likelihood estimation. Following this, I calculated the probabilities of moving across different groups and show them in table 18 and table 20. If the earlier assumption about transaction costs holds, we should be able to see the probability of leaving the equity market (going from any higher group to the bottom group) is smaller for those households positioned originally in a high group than those in a lower group. Further, the probability of staying away from the equity market in both survey years should be large if the household is reluctant to pay any transaction cost, especially entry costs. The first row of table 18 indeed shows this pattern. The probability of holding no stock in 1989 decreases significantly from 90 percent for those holding no stock at all in 1984 to 20 percent for those held the largest amount of stock in 1984. For the period 1989-1994, households with the most stock in 1989 only had a 18 percent chance of leaving the market by 1994, while households with no stock in 1989 had a very high chance (89 percent) of remaining outside of the market. In both cases, the results show that the probability of staying outside the market is around 0.9.

Finally, the chance of jumping to any non-adjacent higher group should also be smaller than that of remaining in the same group or making a one-group move. A brief examination of the probability tables shows that the results are all consistent with these ideas.

Parallel to the results from Hurst, Luoh and Stafford (1998), all of the groups have a substantial probability of exiting the stock market entirely. Even the largest holders of stock have a substantial probability of leaving. From 1984 to 1989, 338 households quit the equity market out of a total of 1,071 households who held stocks in 1984. This is a rate of 31.6 percent, which is rather high. Similarly, from 1989 to 1994, the quitting rate is 28.9%, slightly lower but still at a high level. Those not holding stock are highly unlikely to start holding stock. From 1984 to 1989, only 559 of the 3,813 non-stockholders, or about 14.7 percent, entered the market, about half of the quitting rate. Similarly, only 16.3% of the 3,582 non-stockholders entered the market between 1989 and 1994. Finally, consistent with large proportional transaction costs, small changes are more likely among those holding stock in both years than large changes. However, since the wealth surveys are about five years apart, and the data only show the balances in stock accounts, households could be reshuffling across different groups more than my results indicate.

1.5 Conclusion

In this paper, I empirically demonstrate that even though risky, uninsurable labor income can crowd out stockholding, the effects are not as large as expected. There are three reasons for this. First, as noted by Heaton and Lucas (1997), labor income has a "bottom line" bad result, different from the other financial investments. This can effectively decrease investors' sensitivity to labor income risk. Second, economic theory predicts that, with the presence of background risk, households become much less tolerant to bearing additional stock market risk. However, labor income risk cannot fully reflect the uninsurable background risk faced by households. Finally, the econometric reason is that treating positive labor income flows and zero labor income flows in the same way can translate some non-income risks into labor income risk, thus biasing the effects of income risk. My model shows that when sample selection bias is taken into account, the effects of labor income are trivial.

This paper also shows that household investment is positively correlated with financial intermediation development, as indicated by brokers per capita in the state of residence. This mechanism operates because more brokers per capita in a state can significantly decrease transaction costs and make stock investing more accessible to households. The services of security brokers can decrease transaction costs in several ways. First, a trained professional financial consultant can guide investors in developing sound individual investment plans and accelerate the learning process, thus decreasing information costs. Second, most brokers can provide multi-dimensional investment tools and on-line research facilities; these can help investors to access accounts more easily and trade more strategically. Third, competition among different brokers can decrease monetary commission fees. Last, the growth of broker advertising and services can create a better investment environment and lower marginal costs for new investors. As more investors join the market, more brokers will be attracted and they can provide better and more efficient services. So the stock market investment is self-reinforcing through the intermediation of brokers.

Finally, the Markov chain model shows that, due to the presence of transaction costs, households reduce trading frequencies and exit the market when the capital gains cannot recover per-period participation costs.

CHAPTER 2

2.1 Introduction

After checking and savings accounts, owner-occupied housing is the largest and most important component in household portfolios. Bertaut and Starr-McCluer (2000) use household sector assets and liabilities data from the Federal Reserve Board's Flow of Funds accounts to show that residential property accounted for 20-30% of total household assets during 1983-1998. A similar calculation using Survey of Consumer Finance weighted data shows that primary residence comprises 32% of the average household's total assets. The random sample I constructed from Panel Study of Income Dynamics shows that at least 60% of American households own a house, and the mean value of the house increased from \$65,000 to \$100,000 during the 10-year period from 1984 to 1994.

Researchers have recognized the fact that housing investment can significantly affect household portfolio structure due to the dual roles of housing, which is both a durable consumption good and an investment vehicle. Economists have begun to link the issue of housing investment to the well-known stock market nonparticipation problem. Brueckner (1997) suggests that portfolio inefficiency results from the homeowner's rational balancing of the consumption benefits and portfolio distortion associated with housing investment. Cocco (2000) shows that investment in housing reduces equity market participation for younger and poorer investors due to their limited wealth. House prices also crowd out stock-holding, and this effect is larger for those with less net worth. Flavin and Yamashita (1998) use the mean-variance frontier to show that the consumption demand for housing can generate a life-cycle pattern in the portfolio shares of stocks and bonds.

Despite the wide recognition of the importance of housing investments, housing investments and their interaction with either labor income or other financial assets remain unexplored in the academic literature. In this paper, I show that the interaction of uninsurable labor income and self-reported house value can decrease equity investment. This is because the available financial resources after saving for down payment or mortgage of the house are usually limited, especially for younger and poorer households. Further, if a large residential investment comes together with a riskier labor income flow, the household will feel even more reluctant to bear additional equity risks in the stock market.

A similar covariance term between housing investment return and stock return shows that negative covariance can boost stockholding. Goetzmann (1993) uses a mean-variance framework to show that residential property ownership is relatively stable from the investment point of view since it can reduce the overall portfolio risk. Yao and Zhang (2002) use a dynamic programming model to show theoretically that housing investments can diversify stock market risks for homeowners.

2.2 Data

I continue to use data from the Panel Study of Income Dynamics for household demographics and self-reported house value. The stock market participation information is collected in the wealth supplement, which is administered every five years in PSID. In each survey, the respondent is asked for the present value of his/her house, i.e. how much it would bring if the respondent sells it today. Self-reported house value no doubt is an imperfect measure of transaction value. Skinner(1994) finds, however, that the house value series derived from PSID resembles the measure from the Commerce Department, suggesting that respondents have reasonably accurate and unbiased estimates of the market values of their homes. The labor income risk is evaluated as the residuals from the random effect estimation of household total labor income, based on their human capital. The annual stock market return is measured as the S&P 500 index return with dividends reinvested.

2.3 Model

I use a simple measure of the covariance between labor income risk and self-reported house values:

$$Cov(W_i H_i) = \sum_{t=1980}^{1993} e_{it} H_{it}$$

Where H_{it} is the self-reported house value for household i in year t. e_{it} is residual term from the following model for labor income by Carroll and Samwick (1997)[1]:

$$\ln w_{it} = p_{it} + \varepsilon_{it}$$
$$p_{it} = g_{it} + p_{it-1} + \eta_{it}$$

In each period t, a household *i* with a set of characteristic variables receives labor income w_{it}. In the decomposition of the logarithm of wage income, p_{it} is the permanent component, which is defined as the amount of log labor income the household receives in the absence of any transitory income shocks. In each period, the permanent component grows by a factor *g*. η_{it} is a shock to permanent income and $\boldsymbol{\varepsilon_{it}}$ is a transitory shock to the logarithm of labor income. It is assumed that both permanent and transitory shocks are normally distributed, i.e. $\varepsilon_{it} \overset{iid}{\sim} N(0, \sigma_{\varepsilon i}{}^{2})$, $\eta_{it} \overset{iid}{\sim} N(0, \sigma_{\eta i}{}^{2})$[2]. I further assume that g_{it} can be predicted linearly with a vector $X_{it-1}$of household demographics at time $t-1$. So we can have

$$\ln w_{it} = \ln w_{it-1} + g_{it} + \eta_{it} + \varepsilon_{it} - \varepsilon_{it-1} \qquad (1)$$

From this equation, I calculate the conditional mean and variance of log labor income:

$$E(\ln w_{it} \mid \ln w_{it-1}, x_{it-1}) = \ln w_{it-1} + g_{it}$$
$$V(\ln w_{it} \mid \ln w_{it-1}, x_{it-1}) = \sigma_{\eta i}{}^{2} + 2\sigma_{\varepsilon i}{}^{2}$$

The general procedure[2] in the previous literature is to regress $(\ln w_{it} - \ln w_{it-1})$ on a set of observable and exogenous households characteristics $\boldsymbol{X_{it-1}}$ in each year. The

---

[1] This model was also employed in Viceira(01) and Vissing-J∅rgensen(00).

[2] See also Vissing-J∅rgensen(00) and Angerer (03)

predicted values will be estimates of g_{it}, the residuals will be estimates of $\eta_{it} + \varepsilon_{it} - \varepsilon_{it-1}$, and the sample variance of the residuals will be estimates of $\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2$.

This paper adopts a slightly different approach and treats the problem as a sample selection issue as described in Heckman (1979). In this selection process, a household with a zero income event is included if and only if the household can earn positive wage income. Moreover, because the regression in equation (1) actually involves the selection of both w_{it} and w_{it-1}, this is actually a bivariate sample selection issue. To address this problem, I first run a bivariate probit model to estimate the probability of earning positive income in both years t and t-1 for each household and then calculate their inverse mills ratios by using the bivariate cumulative distribution function and bivariate probability density function. Then I pool all households in all of the sample years and estimate the log difference of labor income using a random effect model, with the variables from the standard human capital model as independent variables, together with the two inverse mills ratios calculated from the bivariate probit model to adjust for sample selection.

The predicted values and residuals can be easily obtained for these households from the above random effect estimation. The residuals e_{it} are used to calculate the covariance between income risks and house prices. The empirical estimation in the paper also controls for expected income and income risks. They are calculated as the following:

$$E(w_{it} \mid w_{it-1}, x_{it-1}) = w_{it-1} e^{g_{it}} e^{\frac{1}{2}(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)}$$
$$V(w_{it} \mid w_{it-1}, x_{it-1}) = (w_{it-1} e^{g_{it}})^2 e^{(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)} (e^{(\sigma_{\eta i}{}^2 + 2\sigma_{\varepsilon i}{}^2)} - 1)$$

Finally, I also control for the covariance between income risks and stock return, which is calculated as $\sum_{t} \Delta \ln w_{it} \bullet R_t$, where $\Delta \ln w_{it} = \ln w_{it} - \ln w_{it-1}$ and R_t is the value-weighted gross return with dividend reinvestment for the S&P500. Note that for those families with zero labor income, I add $1 so they have zero log labor income, since doing this will not change the results.

I use a similar measure to calculate the covariance of stock return and house investment returns:

$$
\begin{aligned}
Cov(SH_i) &= \sum_{t-1980}^{1993} R_t[(H_{it} - H_{it-1})/H_{it-1}]/(1 - M_{it-1}/H_{it-1}) \\
&= \sum_{t-1980}^{1993} R_t(H_{it} - H_{it-1} \big/ H_{it-1} - M_{it-1})
\end{aligned}
$$

Where R_{it} is the annual return for the S&P 500 index with dividends reinvested, M_{it} is the outstanding mortgage balance on the household i's house and H_{it} is the self-reported house value. Previous researchers have used different measures of the "return" to housing investments and treat housing as an asset class, like stocks or bonds. However, housing is distinct from stocks and bonds not only because it represents the largest financial commitment of the household, but also because it provides a flow of consumption services to the household, and it is often a highly leveraged investment. In this paper, I use the self-reported house value and the mortgage balance to calculate the two covariance terms above, hypothesizing that they reflect the homeowner's perception of the riskiness of stockholding.

In the above equation, $1 - M_{it} / H_{it}$ is the ratio of the household's equity to the value of its house. Its reciprocal is therefore the leverage ratio, the factor of proportion between the rate of return on the household's equity and the rate of appreciation of its house. For simplicity reasons, we are not considering the depreciation of the house, assuming that the home owners maintain the house on a regular basis and this is also incorporated into the self-reported house values.

Earlier studies also tried to calculate the covariance term by subtracting the mean from each of the variables, but did not find significant difference in the conclusion. So the results from that version were not shown here.

2.4 Econometric Results

To separate the decision to participate in the stock market from the decision on how much stock to buy when the household has already entered the market, I estimate stock market participation using a Heckman two-stage model. The first step is a probit model for the probability of holding stock, and the second step is a sample selection model for how much stock the investor actually holds. Tables 25 and 26 show the results when the covariance of labor income risk and house value is incorporated. Other regressors include expected labor income and the standard deviation of labor income estimated in the above random effect model. I also include the covariance term between uninsurable labor income and stock returns to test the hedging demand for stock purchase against labor income risk. The other control variables include the age of the household head and dummy variables indicating whether the head is male, works in the financial sector, has at least a college education, has a managerial or professional job, and is white. For identification reason, I include the dummy variable for if the head has a white-collar job in the probit model but exclude it from the sample selection step.

The covariance of uninsurable labor income risk and house value has significantly negative effects on the probability of holding stock and the amount held, conditional on being a stockholder. The explanation of this result is quite intuitive: because buying a residence requires a large monetary investment, the financial resources remaining for stock accounts will be limited for most households, especially younger and poorer households. If a household has a positive covariance between labor income risk and house value, this means a larger self-reported house value comes together with a riskier labor income stream. This will obviously increase the uncertainties of investing in the equity market. The additional risks will be even greater when the household "over-invests" in housing, because of the consumption motivation. And, owning a house requires a large initial investment, causing many households to dissave during a relatively long time period, especially for young and poorer households. A household with a riskier labor income flow will feel even more reluctant to invest in the equity market if they own a larger house and have to pay a mortgage. If the household's portfolio already includes stock, the household may choose to reduce the stock investment or leave the stock market entirely.

Table 27 and table 28 show the econometric results when the covariance of housing investment return and stock index return is introduced into the Heckman model. This covariance term is significantly negative in both steps of the Heckman model, which means that a negative covariance between housing investment return and stock return encourages households to participate in the stock market and to hold more stocks. It should not be surprising since the negative covariance is the diversification effect of the housing investment. Goetzmann and Ibbotson (1990) provide compelling evidence to show that adding residential real estate into a household's portfolio can significantly lower the overall risk of that portfolio. Goetzmann (1993) also uses a mean-variance framework to show that home ownership reduces overall portfolio risk, especially when short-term liquidity is not required, making stock investment more favorable to homeowners. Yao and Zhang (2002) further document that the substitution effect of housing investment for stocks is only obvious for renters, since they have a stronger incentive to save for a down-payment for buying a house, so they must hold a safer portfolio but are trying to benefit from lower future housing service costs.

For homeowners, housing can also be used to buffer equity risks. To supplement this argument, I calculate the mean stock-holding amount for both homeowners and non-homeowners in my PSID sample. Table 29 shows the trend over the 10-year sample period, and stock holding by homeowners is about 7-9 times of that among non-homeowners. The results become clearer when we look at the effect of the age of the household head. In both the probit and sample selection steps, the coefficients for the age of the household are significantly positive in all of the three waves of wealth supplements. For example, in 1994, household heads that are one year older increase their stock ownership by $5445, among households already invested in the stock market. As the head ages, he/she is also typically paying down all mortgages on the housing investment, so the household is enjoying not only the consumption service from owning a house, but also financial security. At this point, the house acts more like a buffer against equity market risks and makes stock investments more favorable than ever.

The effects of labor income risks as estimated in the first chapter remain almost the same after controlling for the two new covariance terms. Expected labor income has almost negligible effects in both steps of estimation as shown in chapter one. The standard deviation of uninsurable labor income risks and the covariance between labor income and stock return show significantly negative effect in the probit model, meaning they could crowd out stock investment; but these crowd-out effects decrease in the sample selection estimation.

These results are consistent with the estimation in chapter one, reinforcing my conclusion that even though labor income risks can indeed crown out stock investment, the effects are not as large as expected; Instead, transaction costs as proxied by broker per capita and the housing investment effects as shown in this section could explain the non-participation in the stock market.

The other demographic control variables in the model have the effects documented in the previous literature. A male-headed household is more likely to buy stock and to hold around $50,000 more if already a stockholder. Most probably this is because male-headed households are less risk averse.

The dummy variable indicating whether the household head works in the finance sector still proxies for job-specific financial information, and it can decrease the time needed for an investor to obtain financial knowledge needed to invest in the stock market.

Having at least a 4-year college degree may be helping investors to become familiar with the equity market and to obtain financial information in a more efficient way. Because education is also an important determinant of wage rate in the human capital model, higher investments among the better-educated households can also be explained by the higher incomes of employees with at least a bachelor's degree.

2.5 Conclusion

In this paper, I use simple measure of the covariance of labor income risk and house value to show that this covariance term can discourage stock market participation, because homeowners with riskier labor income have fewer financial resources available for investment in the stock-market. However, the negative covariance between housing investment return and stock return makes stock investments more favorable. This is due to the diversification effect of homeownership; because home ownership can decrease the overall risk of household portfolios, households are more willing to hold stocks if they already occupy a house.

CHAPTER 3

3.1 Introduction

During the most recent economic downturn, the consumer credit market has experienced the highest default/bankruptcy rate in history. Gross and Souleles (2001) documented that personal bankruptcy filings in the United Stated rose by 75% in the late 1990s, occurring in more than 1% of U.S households. The delinquency and charge–off rates on credit cards rose almost as sharply (Federal Reserve Board of Cleveland (1998)). There have been some leading academic explanations for these trends. One strand argues that excessive credit has been extended to sub-prime borrowers and that they have accounted for most of the rise in credit defaults. The other strand focuses on the decreasing cost of defaulting, including the social, informational and legal costs. Zywicki (2002) shows that the operations of the credit card market and consumer choices are consistent with rational decision-making subject to real world constraints. Bangia, Diebold and Schuermann (2000) look at the default issue from a different perspective and propose that macroeconomic activity should be a central determinant of credit portfolio quality. Carey (2002) shows that average credit portfolio losses during the early 1990s recession is only equal to the 0.5% tail during the expansion. However, these researchers were not able to empirically test their propositions.

The paper extends the current literature in the following ways: First, it tests the theoretical model by Wang and White (2000) where a risk-averse, utility-maximizing consumer will have maximum probability of filing for bankruptcy when labor income drops to zero due to unfavorable macroeconomic conditions. This paper suggests that macroeconomic and employment conditions could significantly affect consumer bankruptcy filings even after controlling for household demographics. The bivariate probit model shows that if the state unemployment rate increases by 1%, the probability of a household filing for bankruptcy will increase by 46%, holding other things constant. This is opposed to the literature, which argues that job market conditions driven by macroeconomic conditions will diminish after controlling for demographics using consumer data. The economic theory also predicts that consumers will default on loans when there are unexpected idiosyncratic income shocks, in order to smooth consumption. The paper also tests the effect of unemployment on consumer default, which is consistent with the consumer life cycle theory. If the state-level unemployment rate increases by 1%, the probability of losing a job will increase by 54%, thus increasing the probability of consumer default by almost 34%.

In addition, the paper uses a Heckit-type sample selection model to show that unemployment could also affect consumer's choice of whether to file for bankruptcy under Chapter 7 or Chapter 13, after controlling for the debt/wealth ratio and demographics. This shows that consumers could make a rational, informed choice between Chapter 7 and Chapter 13 filing, once they have decided to file for bankruptcy. This is consistent with the theoretical set up by Wang and White (2000), but opposed to Whitford (1989), who argues that debtors are unable to make an informed choice between the two chapters.

Last, the paper points out that the results will be useful for both policy-makers and banking regulators. Previous empirical tests have concentrated on Chapter 7 filings. There have been debates in the literature on reform of the bankruptcy codes, especially on whether the current codes should be tightened to reduce bankruptcy and whether Chapter 13 should be made as favorable as Chapter 7. Moreover, the incidence of bankruptcy/defaults could change the general riskiness of consumer loans and consequently could change the risk premium and capital allocation as required by the banking regulators. The results have shown that consumer risk profiles are sensitive to macroeconomics variables such as the aggregate unemployment rate, but consumer credit risk modeling has assumed a constant macro economic environment. This time-homogeneity assumption could be damaging to the efficient operation of financial institutions. Gross and Souleles (2001) use panel data on credit card accounts to show that credit risk models miss some systematic and time-varying factors. More sophisticated measures of credit risk will create a competitive advantage through better risk pricing and capital allocation.

This paper is organized as follows: The first section presents the theoretical model of Wang and White (2000) on consumer bankruptcy and the life cycle model by Lawrance (1995), which explains consumer default behavior. The second section uses

PSID data to show that employment conditions are one of the important determinants of consumer bankruptcy filings and delinquencies in paying bills, remaining significant even after controlling for demographics. A sample selection model is also applied in this section to examine the choice between Chapter 7 and Chapter 13 once the consumer has already decided to file for bankruptcy. Previous empirical studies have concentrated on either combined filings or Chapter 7 filings only. This study shows that households filing for Chapter 7 have a significantly higher debt/wealth ratio and a higher chance of being unemployed, which makes the debt consolidation plan as required by Chapter 13 unfavorable. The third section concludes, pointing out that the empirical results have implications for policymakers in reforming bankruptcy law. The previous discussion attributes the increase in bankruptcy in part to the passage of the current bankruptcy code in 1978, and especially the debt exemptions that it provided in Chapter 7.

I also point out that consumer risk profiles will shift after loan origination if aggregate employment conditions deteriorate. Ignoring this time-varying factor when credit risk is modeled could distort proper decision-making and introduce unexpected credit loss. This will also affect compliance with Basel II capital regulations, as banks will experience abrupt and unexpected loan losses if unfavorable aggregate conditions increase consumer defaults or bankruptcy.

3.2 Theoretical Models

3.2.1 The Model on Consumer Bankruptcy Filings

Skyrocketing consumer bankruptcy filings and commercial bank loan defaults have been observed in recent years, and a large academic literature has attempted to explain the phenomenon. Most of the papers have concentrated on explaining the nature of the credit market or the rational usage of credit by consumers. Zywicki (2002) demonstrated that both the operations of the credit card market and consumer choices are consistent with rational decision-making subject to real-world constraints. In this paper, I use a bivariate probit regression model and PSID household survey data to show that being employed could significantly decrease consumer bankruptcy filings and default behavior, even after controlling for household demographic variables. This is an empirical test of the model presented by White and Wang (2000). In this paper, I present a theoretical model following Wang and White (2000), where the likelihood of consumer filing for bankruptcy increases with decreasing labor income and is maximized when the labor income drops to zero.

This is a two-period model where a risk-averse representative consumer maximizes utility. In the first period, the consumer works for N_1 hours with hourly rate w, her total earnings are $Y_1=w*N_1$, and her wealth is W_1. W_1, Y_1, N_1 and w are known for certain. In this period, the consumer also borrows amount B, with an interest rate r. She does not know her wealth W_2 in the second period at this time; it is uncertain with a distribution function $f(w_2)$. At the beginning of the second period, W_2 is realized; N_2 is determined endogenously. The loan is also due in the second period, and the consumer needs to make a debt repayment decision. If she files for bankruptcy, there is a fixed cost of cW_2, where c is a constant with $0<c<1$. According to bankruptcy law, there is also a wealth exemption of E, which is a fixed dollar amount defined by the state where the consumer files for bankruptcy. The consumer must give up all non-exempt wealth above this threshold. The representive consumer could keep her wealth if $W_2<= E$. This implies that if the consumer files for bankruptcy, her total wealth in the second period will be $W_2(1-c)-\max[W_2-E, 0]$. If she chooses not to file for bankruptcy, her total wealth will be $W_2 - B(1+r)$. Her lifetime expected utility could be represented as:

$$
\begin{aligned}
EU &= U(W_1 + wN_1 + B, N_1) \\
&+ \int_0^E U(W_2(1-c) + ewN_2, N_2) f(w_2) dw_2 \\
&+ \int_E^{\tilde{W}_2} U(E - cW_2 + ewN_2, N_2) f(w_2) dW_2 \\
&+ \int_{\tilde{W}_2}^{\infty} U(W_2 - B(1+r) + wN_2, N_2) f(w_2) dw_2
\end{aligned}
$$

In this function, e is the post-bankruptcy earnings exemption, which is a proportion of period 2 earnings Y_2. Under Chapter 7 bankruptcy procedures, all post-bankruptcy earnings can be exempted from debt paying, so we have e=1. Under Chapter 13 procedures, debtors are obligated to repay their debt using a portion of their earnings, so $e<1$. The borrowers second period earnings will be eY_2 if she chooses to file for bankruptcy, while $e<=1$. Her earnings will be Y_2 if she chooses not to file for bankruptcy.

The first term is the utility in the first period. The second term is her expected utility if filing for bankruptcy in the second period, and her wealth is fully exempted from repaying. The third term is the expected utility if the consumer's wealth is greater than the exemption and is used for repaying part of the debt after filing for bankruptcy. The last term is the expected utility if the consumer chooses not to file for bankruptcy.

In the utility maximization context, the consumer will choose to file for bankruptcy in the second period if:

$$W_2 <= \tilde{W}_2$$

where $\tilde{W}_2$ is a threshold that depends on the level of income.

$$\tilde{W}_2 = (E + B(1+r) - (1-e)Y_2)/(1+c)$$

There are important implications of this solution function. First, the threshold is decreasing when earnings in the second period increase. The probability of filing for bankruptcy is the highest if $Y_2=0$. In this theoretical setup, having zero income will maximize the probability of filing for bankruptcy. However, due to the limitations of the data in the empirical tests, we will be unable to rank order the probability of filings, given different levels of income, as we could do in a simulation. A practical solution is to test whether unemployment significantly increases bankruptcy filings given a certain set of household characteristics.

3.2.2 The Theory on Which Chapter to File for Bankruptcy

The model in Wang and White (2000) as above does not discuss directly the choice between Chapter 13 and Chapter 7 filings once the consumer has already decided to file for bankruptcy. However, this issue has been a critical question given the totally different nature of the choices under the current bankruptcy codes. According to the current bankruptcy law, Chapter 7 filing can eliminate all or most unsecured debt, which includes debts on credit cards, medical bills and most personal loans. The debtor cannot keep any significant equity in property, however; she must turn over all of her assets above a fixed exemption level to the Bankruptcy Court in return for the discharged debts. In this sense, the debtor gets a “fresh start” by filing for Chapter 7 bankruptcy. A bankruptcy trustee then sells all the debtor’s non-exempt assets and uses the proceeds to repay her debts on a pro rata basis. Under Chapter 13 procedures, the consumer consolidates all debts through an interest-free debt repayment plan over the next 3-5 years. Under Chapter 13 filings, borrowers must repay unsecured debts at least in an amount at least equal to that the creditors would have received under a Chapter 7 filing. To file under Chapter 13, the debtor must be working or have a consistent income source in order for the court to approve the repayment plan, but she does not have to give up her current assets. This suggests that the consumer is much more likely to file for Chapter 7 bankruptcy if she is unemployed and has relatively low wealth.

There has been some academic discussion of this issue in the economic literature. Domowitz and Sartain (1999) show that higher levels of equity relative to debt push borrowers into Chapter 13 filing with a probability double that estimated for low-equity households. They also show that other household demographics like higher income and a higher employment rate could encourage Chapter 13 filing over the discharge under Chapter 7. This is because under Chapter 7 filing, the borrower must give up all nonexempt assets in return for being able to keep future income and must maintain minimum consumption level; homeownership is not protected.

Li and Sarte (2004) show that for utility-maximizing consumers, the value function of a Chapter 7 bankruptcy filer is invariant to the level of wealth above the exemption level E, as all assets above this level are surrendered. However, when household wealth is high, Chapter 13 filing could dominate Chapter 7 filing. They also show that the value function of households filing under Chapter 13 decreases as debt holdings increase, as higher debts imply a higher debt burden and reduce the available resources for consumption.

Evaluating consumers' choices between Chapter 13 and Chapter 7 filings have important implications for policy-makers. Many proposals for reform focus on bankruptcy choices, in particular asking whether Chapter 13 filings should be encouraged. The Gekas Bill has proposed forcing all bankrupt consumers with income above the median level to repay debt using their post-bankruptcy earnings above a predetermined threshold. This potential change in bankruptcy code would affect the likelihood that consumers will file for bankruptcy, which in turn could affect credit demand and supply and the overall economy.

3.2.3 The Model and Theories of Consumer Defaults

Over the past twenty-five years, the U.S economy experienced a historical increase in personal bankruptcy and a rise in rate of consumer defaults over the past 25 years. In 1996, bank credit card delinquencies exceeded 3.5 percent – the highest delinquency rate since 1973, when statistics were first collected. By 2001, the default rate on credit card loans was about 5 percent.

The academic literature has attributed the record high in consumer defaults to the cyclical state of the economy and unexpected job loss. Lawrence (1997) shows that credit card defaults and personal bankruptcy filings have exhibited strong countercyclical components, moving upward in recessions and downward in economic booms. Hayashi (1987) observes that defaultable debt provides a mechanism for insuring future income. The borrower will choose to default in the low-income state in return for an actuarially higher payment in the high-income state.

Lawrence (1995) use a life cycle model to explain why a consumer chooses to default in the presence of unexpected income loss. In her model, consumers maximize expected life-time utility, and the momentary utility function is of the constant relative risk aversion (CRRA) form with the properties that $U' > 0$ and $U'' < 0$. To simplify the analysis, assume the consumer lives for two periods. Income in the second period is uncertain with an exogenous probability q that income will be zero. The borrower could increase her first period consumption by x_1 through taking a loan, which is due in the second period for x_2, where $X_2 = X_1(1+R)$, R being the interest rate.

In this model, the no-default restriction in the usual life cycle model must be relaxed, the reason is that if banks could legally and easily have claims to all the resources held by the borrower. In this case no consumers would borrow, as there is always a positive probability of earning zero income in the second period, leading to zero consumption.

Within this setup, the consumer maximizes expected lifetime utility, and a zero saving – zero borrowing solution is never optimal. Instead, the risk-averse borrower chooses to borrow a positive amount in the first period. In the second period, if the consumer experiences an unexpected loss of income, he will choose to default on the loan in order to sustain a higher consumption level. The intuition is that consumers with high a idiosyncratic income have lower marginal utility on additional consumption, so they choose to pay back the loan, while consumers with a low idiosyncratic income have to default in order to maintain their minimum consumption level.

The model's result is consistent with some previous observations in the U.S. consumer loan markets. Borrowers with low income do have a higher rate of delinquencies (U.S. National Commission on Consumer Finance (1972)). Sexton (1977) used a segmentation approach to show that low-income families with similar social and demographic characteristics have significantly higher credit card default rates. Rampini (2004) use a one-period model to show that default could allow consumers with unexpected idiosyncratic income shocks to repay less, and thus default acts like insurance. Default penalties thereafter insure that only those consumers will default. He also shows that default rates vary counter-cyclically with macroeconomic aggregations.

It is important to examine consumer defaults from an empirical perspective for two reasons: First, changes in the number of personal bankruptcy filings in the United States follow exceedingly closely with changes in the rate of credit card delinquencies. Lawrence (1997) pointed out that a change in the rate of delinquency leads a similar change in the rate of bankruptcy by about three months. He used aggregate data to show that the 1990s have seen an astonishingly tight relationship between credit card delinquencies and bankruptcy filings. Second, in the face of the current record levels of consumer defaults and bankruptcy, representatives of the retail credit industry have called for changes in the bankruptcy law to limit the dischargeability of credit card debts in bankruptcy filings. Studying the reasons for consumer defaults could help policymakers to evaluate the potential effects of such proposals.

3.3 Empirical Tests

The Panel Study of Income Dynamics (PSID), conducted by Michigan University since 1968, is a longitudinal survey of randomly sampled American individuals and the households in which they reside. The survey concentrates on dynamic aspects of household economic and demographic behavior. The 1996 wave of PSID family study has questions on household bankruptcy filing, including “Have you ever filed for bankruptcy?” and “What was the reason for filing bankruptcy?” By looking at the bankruptcy data together with household demographics and state-level unemployment rate, we can use bivariate probit regression to see how job market conditions affect bankruptcy filing while holding demographics constant. The same wave of the PSID core family survey also includes questions on credit delinquency. I use a similar bivariate probit model to estimate how unemployment affects consumer default while holding household demographics constant. Examining consumer default has further empirical implications. First, personal bankruptcy is always preceded by delinquency, so looking at the trend of bill payment delinquency should help us to understand bankruptcy better. In addition, both bankruptcy and delinquency have been of interest to academics, policymakers and banking regulators.

In this section, I use PSID data to empirically test the propositions in the previous section, and I show that unemployment conditions can significantly increase both the probability that a consumer will file for bankruptcy and the probability of bill delinquency. There have been some disputes in the literature about macroeconomic effects on consumer delinquency and bankruptcy filing. Gross and Souleles (2002) argue that the state unemployment rate should be insignificant after controlling for household demographics. To investigate these issues, I estimate a bivariate probit model using PSID bankruptcy data. In the first equation, both household demographics and state-level unemployment rate affect the probability of the household head being unemployed. In the second equation, household demographics, together with the binary variable of whether the head is unemployed, jointly determine the probability of the household filing for bankruptcy (or becoming delinquent). Instead of using state-level unemployment rate in the second equation directly, this variable serves as an instrumental. The model is as follows:

$$Y_{1i} = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_I$$

$$Y_{2i} = \alpha + \beta_1 X_{1i} + \beta_2 Y_{1i} + \varepsilon_I$$

Where Y_{1i} is the (0, 1) binary variable of whether the i-th consumer was unemployed, X_{1i} is a vector of household demographics, X_{2i} is the state-level unemployment rate in 1996, and Y_{2i} is a binary variable that indicates whether the household head filed for bankruptcy (or whether the household was delinquent in paying bills).

In the 1996 PSID core family survey, a total of 8327 households were interviewed. Eliminating the 20 households who did not respond to the bankruptcy/delinquency questions, we have 8307 households left in the sample. Of these, 526 households (6.33% of the sample) filed for personal bankruptcy. Of the ever-bankrupt household heads, 32% state that job loss was the most important reason they filed for bankruptcy.

Using Full Information Maximum Likelihood (FIML) estimation of the bivariate probit model, we examine how the employment conditions have affected household bankruptcy filings; results are shown in table 32. As family income and state bankruptcy wealth exemptions could also significantly affect consumer bankruptcy filings per previous discussion in the economic literature, the bankruptcy function controls for total family income, state exemption level and demographics. As expected, higher family income could discourage bankruptcy filing, while higher exemption levels can encourage bankruptcy as the households can have more post-bankruptcy wealth. In this table, we also see that the age, sex, marital status, number of children and being Caucasian are the most important demographic variables in determining the probability of being unemployed. I find that the age of the household head is negatively correlated with probability of bankruptcy filings. This is consistent with the results of Fay, Hurst and White (1998). This is because older household heads have accumulated more wealth relative to their debt level and demand less credit. The race variable is also included, as previous studies have found that African-American households are more likely to be turned down for a loan and have less access to credit. There are also unobservable effects, especially those coming from macroeconomic conditions. Using the state-level unemployment rate as the instrumental variable can capture this. In the second equation, we see that only the age of the household head and his/her employment situation significantly affect bankruptcy filing. For the purpose of identification, the state-level unemployment rate only enters the first equation, but not the second. The correlation coefficient of the disturbance terms is about 78%.

We also estimated consumer default using the same PSID sample. Of the 8,307 households from 1996 core family survey, 2,086 have been delinquent on bills. A similar bivariate probit model shows that unemployment is an important determinant of delinquency.

Given the heated discussion on the financial benefits of Chapter 7 filing vs. Chapter 13 filing, we are interested in testing what motivates consumers to file for Chapter 13 bankruptcy instead of Chapter 7, which could eliminate all unsecured debts. The model is based on Heckit-type sample selection. The first step is the bivariate probit model described above, which gives an estimated probability of filing for bankruptcy for each of the households in the sample. The inverse mills ratio is calculated as one over the probability of filing for bankruptcy. The second step is a probit analysis of those households who actually filed for bankruptcy. The inverse mills ratio is added in the second step as an additional regressor to eliminate sample selection bias.

Shown in table 37, the results indicates that the only significant household demographic variable is the age of the household head. The other determinants that could drive Chapter 13 filing are the debt/wealth ratio and employment status. In this paper, as data on household total equities in year 1996 are not available, I use the value of the house plus total family income as a proxy for wealth. Having a lower debt relative to wealth could significantly increase the probability of Chapter 13 filings. This is because

Chapter 13 requires the debtor to consolidate all debts, which would not be financially beneficial if the debt level is very high and the household does not have much equity. The household would be better off eliminating all unsecured debt through Chapter 7 filing. However, if the household has relatively low debt and substantial wealth (a valuable house), it is better to keep the house by filing for Chapter 13 bankruptcy and to repay the low unsecured debts through the interest-free repayment plan. Further, Chapter 13 also requires the household to have consistent income for the next 3-5 years, in order to pay back the consolidated debts. This will pose a problem for consumers whose income is low and volatile. This type of household would be much better off giving up all assets at the time of filing for Chapter 7 bankruptcy, especially if household wealth is at or below the wealth exemption level E.

3.4 Conclusion

This paper examines a theoretical bankruptcy model by Wang and White (2000), in which the probability of filing for personal bankruptcy is a decreasing function of income, and this probability is maximized when the income level drops to zero due to unemployment or any other unexpected job loss. The solution to the model also implies that a risk-averse consumers with high unsecured debts, low property and low expected income will prefer filing for Chapter 7 bankruptcy over Chapter 13 bankruptcy. The assumption is that Chapter 7 filing will eliminate most of the unsecured debts, given that the consumer relinquishes all her wealth above a certain exemption level. This is to give a "fresh start" to the debtor. Under Chapter 13 filing, the consumer can keep his/her properties, but s/he must consolidate all debts in an interest-free debt repayment plan, to be paid off out of earnings over the next 3-5 years. The model shows that this will decrease the marginal utility of purchasing power in the future periods. Given that the consumer can always choose between Chapter 7 and Chapter 13, the model implies that the consumer will prefer filing for Chapter 7 bankruptcy when her debt is much higher relative to the wealth level, or when she is facing a possible post-bankruptcy unemployment situation.

The paper uses bankruptcy and delinquency data from Panel Study of Income Dynamics to empirically test these propositions. Using a bivariate probit model, I show that unemployment could significantly affect the probability of bankruptcy filing, even after controlling for demographics. Using a Heckit-type sample selection model, I also focus the analysis on households who have already filed for bankruptcy. For the choice between Chapter 7 and Chapter 13 filing, the debt/wealth ratio and unemployment dummy variables are the most important determinants of filing for Chapter 7, as predicted by the theory. Household demographics do not significantly affect this choice.

As consumer bankruptcy is usually preceded by delinquency in paying bills, the paper also empirically tests the effect of unemployment on delinquency using PSID data and the bivariate probit model. The consumer life cycle theory (Lawrance (1995)) predicts that consumers choose to default when there is unexpected income shock, in order to smooth consumption. The unemployment rate enters the equation significantly with a positive sign, showing that probability of default is reduced by about 30% if the head of the household has consistent earnings.

The results have important implications for policy-makers. There has been long discussion on bankruptcy code reform. Part of the discussion has centered on whether the 1978 Bankruptcy Code caused the increase in the number of filings observed in recent years. Previous studies have concentrated on Chapter 7 filings, due to the financial benefit of this part of the code. This paper has been able to study both the bankruptcy decision and the decision on which chapter to file once the household has decided to declare bankruptcy. Controlling for household demographics and assuming consumers are rational decision makers, the results show that the number of filings will increase significantly if the unemployment rate is higher than usual, as was the case during the most recent economic downturn.

There have also been debates on whether to change Chapter 13 codes, as Whitford (1989) argues that debtors are unable to make an informed, self-interested choice between Chapter 7 and Chapter 13. However, the empirical tests in this study show consumers do choose in which chapter to file according to their debt/wealth ratio and employment conditions. Even though Chapter 13 does not give a “fresh start” as Chapter 7 does, it does indeed help debtors to retain assets, which is more favorable if the consumer has relatively less debt in his/her portfolio and also has a consistent income source to accommodate the interest-free debt repayment plan.

The results may also be useful to banking regulators. Currently, most consumer credit risk policies have assumed time-homogeneity and work very well under benign economic conditions. As I have shown in the previous section, consumer risk profiles and default behavior are significantly impacted by macroeconomic conditions. This personal default and bankruptcy issue affects credit markets and becomes more important given that current credit risk methodologies are not sensitive enough to provide a cushion to unexpected credit loss during an economic downturn. This is mainly reflected in the risk based pricing and credit capital allocation area.

Currently, credit-scoring techniques based on logistic regressions have been widely adopted in credit origination and risk based pricing, but decision-making is dependent only on borrower risk profiles at the time of origination. However, the actual propensity to become delinquent or bankrupt after origination is affected by changes in social and economic factors. Unexpected job loss, a change in interest rate and a change in house price can all make default and delinquencies more or less likely. Even though these factors affect default probabilities through different channels, they are similar in how they are all correlated with business cycles. This challenges the traditional logit model, in which the default probabilities are modeled as a function of risk profiles at the point of origination. The model is thus static and does not reflect how changing macro economic conditions affect risk profiles and default probabilities.

The empirical results in this paper also have implications for bank regulators as they are trying to prepare their standards for new Basel II regulations of capital. In the proposed capital accord, lower-rated assets will require more capital in both the standardized and, especially, the internal-rating-based (IRB) approach as they have higher probability of default. Given the nature of credit scoring models, the assumption seems to be that the proportion of lower-rated assets is a direct estimate of the probability of default. However, the key challenge is a mechanism to align estimated, rank-ordered probabilities from the logistic regression output to the actual probability of default. This challenge still comes from the underlying assumption behind the logistic regression approach: the scoring model is not truly "forecasting" in nature as the model usually cannot incorporate the changing economic environment over the forecast period, nor can it reflect the changing risk profiles of customers.

Second, even though the increased risk sensitivity brought in by the Basel II model has important benefits for capital allocation within and across banks, it also raises significant problems when considered across different economic regimes. Capital volatility over time is increased materially under the new accord. Ervin and Wilde (2004) noted that the impact of the capital ratio under the new regulation is approximately six times the impact under the previous guidelines, a major increase in capital volatility. They also observed that similar effects occurred in all rating grades and different years where adverse credit conditions were present. This could have important effects on the overall economy if banks in aggregate are forced to change their lending behavior to maintain their capital ratios at times of economic stress. If banks respond by restricting new lending, the supply of available credit will be reduced during the adverse part of the credit cycle. This could amplify, not reduce, credit cycles and potentially exacerbate economic swings. Ervin and Wilde (2004) proposed to flatten the IRB curve, which essentially reduces risk sensitivity, the guiding philosophy of the new accord. The choice of how to address the volatility of capital in response to credit risk is ultimately is a question of how to achieve a balance between these issues and is an important topic for further research.

In summary, developments in consumer credit are influencing, and are being influenced by, the efforts to comply with the New Capital Accord. This paper uses household survey data to show that consumer delinquency and bankruptcy filings are significantly affected by employment conditions, and the results remain significant even after controlling for household demographics. The results are useful to both policymakers and credit risk regulators. The results demonstrate that ignoring changing macroeconomic factors and the related changes in consumer risk profiles in credit risk modeling can affect proper risk pricing of consumer loans and mis-specify the capital allocations required by Basel II regulations.

APPENDIX A

Year	1+r(d)	1+rf	Risk Premium
1946	0.906658208	1.003520667	-0.096862459
1947	1.049099673	1.004611532	0.044488141
1948	1.05264885	1.009790525	0.042858324
1949	1.182481032	1.011060663	0.171420369
1950	1.327613229	1.012133911	0.315479318
1951	1.234046981	1.014833804	0.219213177
1952	1.19004508	1.016420038	0.173625042
1953	0.982484084	1.017799989	-0.035315905
1954	1.526027088	1.008626765	0.517400323
1955	1.313576	1.015550823	0.298025177
1956	1.064444524	1.024214066	0.040230458
1957	0.888119003	1.031286709	-0.143167706
1958	1.438021932	1.014150822	0.423871111
1959	1.129369198	1.028153045	0.101216154
1960	1.001820345	1.0258238	-0.024003455
1961	1.276447199	1.021590553	0.254856646
1962	0.912089833	1.027240959	-0.115151126
1963	1.226379669	1.031513844	0.194865825
1964	1.1666507	1.035182655	0.131468045
1965	1.125001028	1.03972945	0.085271578
1966	0.897540618	1.047050798	-0.14951018
1967	1.241123366	1.041474461	0.199648905
1968	1.10998578	1.052942362	0.057043418
1969	0.91670554	1.065912057	-0.149206517
1970	1.041018664	1.0638294	-0.022810736
1971	1.141730778	1.043172012	0.098558766

Continued

Table 1. Risk Premium 1946-1999

Continued

Year	1+r(d)	1+rf	Risk Premium
1972	1.191400002	1.038911708	0.152488295
1973	0.852494969	1.070585837	-0.218090868
1974	0.736007706	1.080780976	-0.34477327
1975	1.372639552	1.058210171	0.314429381
1976	1.239763146	1.051556818	0.188206329
1977	0.927358136	1.051521258	-0.124163122
1978	1.064952012	1.073080935	-0.008128924
1979	1.187787225	1.106898517	0.080888707
1980	1.325972291	1.115247491	0.2107248
1981	0.949636063	1.148557601	-0.198921538
1982	1.220488071	1.1066428	0.113845271
1983	1.223854449	1.088470949	0.1353835
1984	1.067456748	1.099557084	-0.032100335
1985	1.319986648	1.076767266	0.243219382
1986	1.183924377	1.060570636	0.123353741
1987	1.053354028	1.053845159	-0.000491131
1988	1.168676267	1.06322796	0.105448306
1989	1.313366729	1.08220572	0.231161009
1990	0.968091559	1.076798851	-0.108707292
1991	1.306724801	1.055064749	0.251660051
1992	1.077210882	1.034015233	0.043195649
1993	1.098706303	1.028994155	0.069712148
1994	1.013513096	1.038799737	-0.025286642
1995	1.376601951	1.055318041	0.32128391
1996	1.232089217	1.051449479	0.180639738
1997	1.33614442	1.054239237	0.281905182
1998	1.293194924	1.047811079	0.245383845
1999	1.215212214	1.045608211	0.169604002
average	1946-1999	0.09324783	
	1980-1994	0.077479795	

Reason for deletion from sample	N
Latino over-sample	9175
Split-off families since 1979	5509
Non-response family	4886
Asset income be top-coded	4884

Table 2. Sample Selection Criterion

	1984	1989	1994
Family labor income	26266	35480	41983
Age of head	43	48	53
Age^2 of head	2049	2485	2910
If the head has at least college edu	0.33	0.38	0.36
If the head has a white-collared job	0.31	0.32	0.31
If the head is white	0.64	0.66	0.65
How many children in the family	1.24	1.09	1.15
If the head is male	0.73	0.72	0.73
If the head works in the financial company	0.06	0.07	0.07
If the head works in other services	0.28	0.26	0.25
Number of kids the head has	2.84	-	-
Brokers per capita	0.0007	0.0009	0.001
Per capita income	13476	13842	21560
Expected labor income	44593	44593	44593
Stdev. Of labor income	301508	301508	301508
Cov(income , stock)	-1.39	-1.39	-1.39

Table 3. Variables Used and Their Mean Values

	1984	1989	1994
Number holding checking or savings accounts	3545	3690	3386
Percentage of checking/savings account ownership in the sample	72.5%	75.5%	69.3%
Mean value of checking and savings accounts among those who hold such accounts	$12273	$19539	$26328
Median value of checking and savings accounts among those who hold such accounts	$2983	$4700	$6500

Table 4. Trend of Household Checking/Savings Account Ownership from PSID 1984-1994
(Total Number of Households: 4884)

	1984	1989	1993
Number holding checking or savings accounts	3042	3303	3393
Percentage of house ownership in the sample	62.3%	67.6%	69.5%
Mean value of house among those who hold such accounts	$63439	$93145	$102339
Median value of house among those who hold such accounts	$54545	$65000	$75000

Table 5. Trend of Household House Ownership from PSID 1984-1993
(Total Number of Households: 4884)

	1984	1989	1994
Number holding stock	1071	1292	1501
Percentage of stock holding	21.9%	26.5%	30.7%
Mean value of stock holding among stockholders	$23813	$40951	$86094
Median value of stock holding among stockholders	$5500	$10000	$27000

Table 6. Trend of Household Stock Holding from PSID 1984-1994 (Total Number of Households: 4884)

	1995	1994
intercept	0.1599 (0.3413)	-0.5302 (0.3285)
age	0.0302 (0.0125)	0.0457 (0.0120)
Age^2	-0.0006 (0.0001)	-0.0007 (0.0001)
Education of the head	0.0505 (0.9653)	0.0535 (0.0658)
If the head has a white-collared job	0.3162 (0.0784)	0.3664 (0.0803)
If the head is white	0.1017 (0.1698)	0.0598 (0.1641)
If the head is employed	1.4632 (0.0643)	1.6551 (0.0654)

Rho=0.8108

Table 7. Bivariate Probit Model for Positive Labor Income in Both Years (Using 1994 and 1995 as an Example)

Variable	Parameter estimate (standard deviation)
Head age	-0.0118 (0.0009)
Head Age square	0.00003 (0.000009)
College education or above (head)	0.0240 (0.0098)
Managerial occupation (head)	-0.0092 (0.0117)
If the head is white	-0.0327 (0.0085)
Inverse mills ratio 1	0.0785 (0.0038)
Inverse mills ration 2	$-3.4463*10^{-28}$ (0.0000)

Table 8. Random Effect Model of Difference of Log Labor Income on Household Demographics, Adjusted by Bivariate Sample Selection Criterion

Variable	1984	1989	1994
intercept	-2.4933 (0.1115)	-2.4973 (0.1192)	-1.8827 (0.1112)
E(labor income)	$-4.1380*10^{-14}$ $(5.090*10^{-13})$	$2.0996*10^{-14}$ $(4.07*10^{-13})$	$5.2118*10^{-13}$ $(3.420*10^{-13})$
Std(labor income)	-0.0780 (0.0216)	-0.1109 (0.0205)	-0.1651 (0.0189)
Cov($\Delta \ln w_{it}$, R_t)	-0.0171 (0.0058)	-0.0184 (0.0057)	-0.0183 (0.0052)
If the head is male	0.3452 (0.0597)	0.3337 (0.0564)	0.4261 (0.0592)
If the head is in financial firms	0.1542 (0.0846)	0.3340 (0.0784)	0.2197 (0.0789)
If the head is in other services	0.2206 (0.0508)	0.1979 (0.0516)	0.1865 (0.0519)
Age of head	0.0118 (0.0019)	0.0131 (0.0019)	0.0146 (0.0017)
If the head has a college or above degree	0.5224 (0.0505)	0.6865 (0.0483)	0.4724 (0.0444)
If the head has a management or professional job	0.4510 (0.0514)	0.3270 (0.0504)	0.5406 (0.0462)
If the head is white	0.7373 (0.0575)	0.7878 (0.0562)	0.7133 (0.0560)
Total number of children of the head	-0.0001 (0.0026)	-0.0080 (0.0030)	-0.0067 (0.0027)

Table 9. Probit Analysis of Stock-holding Probability (With Standard Deviation in Brackets)

	1984	1989	1994
E(labor)	0.0011	0.0007	0.0192
Std(labor)	-0.0260	-0.0416	-0.0717
Cov(labor, Return)	-0.0205	-0.0253	-0.0296

Table 10. Change in Probability if Any of the Following Regressors Is Changed by One Standard Deviation while the Other Characteristics Remain at the Sample Mean

Variable	1984	1989	1994
intercept	-451237 (197856)	-548555 (252727)	-519412 (383713)
E(labor income)	$-2.9344*10^{-8}$ $(1.0*10^{-7})$	$1.0*10^{-6}$ $(3.0*10^{-7})$	$3.0345*10^{-8}$ $(7.0*10^{-8})$
Std(labor income)	-5198 (4718)	-17233 (8984)	-21823 (23019)
Cov($\Delta \ln w_{it}$, R_t)	-1520 (1054)	-3057 (1730)	-6092 (3352)
If the head is male	54027 (20017)	55402 (26232)	70062 (27314)
If the head is in financial firms	24644 (10027)	50572 (24759)	28354 (23689)
If the head is in other services	25528 (12027)	45234 (16600)	21627 (10017)
Age of head	2318 (651)	3832 (935)	5389 (1906)
If the head has college or above degree	72381 (28441)	104575 (48497)	47169 (58556)
If the head has a management or professional job	52630 (24535)	47251 (23721)	79651 (36480)
If the head is white	87301 (42664)	107891 (60128)	86842 (43069)
Inverse mill's ratio	151143 (75237)	160997 (97606)	150867 (180753)

Table 11. Heckman Two-Stage Analysis of the Amount of Stock-Holding

Variables	1984	1989	1994
intercept	-2.5420 (0.1129)	-2.5086 (0.1199)	-1.9468 (0.1129)
E(labor)	$-4.0320*10^{-14}$ ($5.13*10^{-13}$)	$1.8540*10^{-14}$ ($4.12*10^{-13}$)	$5.3202*10^{-13}$ ($3.51*10^{-13}$)
Std(labor)	-0.0772 (0.0217)	-0.1098 (0.0205)	-0.1665 (0.0190)
Cov($\Delta \ln w_{it}$, R_t)	-0.0178 (0.0059)	-0.0185 (0.0057)	-0.0190 (0.0053)
If the head is male	0.3323 (0.0600)	0.3356 (0.0565)	0.4265 (0.0592)
If the head is in financial firm	0.1589 (0.0848)	0.3384 (0.0786)	0.2203 (0.0788)
If the head is in other services	0.2345 (0.0511)	0.2008 (0.0518)	0.1872 (0.0522)
Age of head	0.0120 (0.0019)	0.0131 (0.0019)	0.0144 (0.0017)
If the head has college or above degree	0.5240 (0.0508)	0.6823 (0.0485)	0.4718 (0.0446)
If the head has a managerial/ professional job	0.4576 (0.0517)	0.3296 (0.0506)	0.5432 (0.0463)
# of children the head has in 1984	-0.0003 (0.0026)	-0.0080 (0.0030)	-0.0068 (0.0027)
Race of the head	0.7421 (0.0583)	0.7905 (0.0566)	0.7146 (0.0562)
Brokers per capita	0.0351 (0.0199)	0.0090 (0.0171)	0.0547 (0.0143)

Table 12. Probit Analysis with Transaction Costs

	1984	**1989**	**1994**
Brokers per capita	0.0007	0.0002	0.0215

Table 13. Change in Probability If Brokers per capita Is Changed by 1 Standard Deviation while the Other Characteristics Remain at the Sample Mean

	1984	1989	1994
intercept	-413919 (194474)	-561489 (250913)	-606999 (395782)
E(labor)	$3.2219*10^{-8}$ ($0.012*10^{-5}$)	$0.0015*10^{-3}$ ($0.031*10^{-5}$)	$4.1761*10^{-8}$ ($0.007*10^{-5}$)
Std(labor)	-4107 (4575)	-17545 (8854)	-25848 (23417)
Cov(Δlnw_{it}, R_t)	-1351 (1064)	-3106 (1716)	-6946 (3439)
If the head is male	48705 (18804)	55606 (26131)	70163 (27218)
If the head is in financial firms	23316 (10018)	51828 (24807)	29712 (23617)
If the head is in other services	24267 (12307)	46266 (16616)	21740 (10015)
Age of head	2198 (640)	3855 (927)	5374 (1911)
If head has college or above degree	66672 (27653)	106059 (47747)	57960 (59154)
If head has management or professional job	47936 (24122)	47999 (23705)	79931 (36476)
Race of the head	80504 (42245)	110265 (59605)	88145 (43045)
Brokers per capita (1 out of 1000 population)	2812 (2263)	3933 (3535)	12637 (8000)
Inverse mill's ratio	134919 (73054)	164830 (96693)	186971 (183171)

Table 14. Heckman Two-Stage Analysis with Brokers per capita

Variables	1984	1989	1994
intercept	-2.8180 (0.1826)	-2.4918 (0.1695)	-1.9580 (0.2074)
E(labor)	$-5.32*10^{-14}$ ($5.5*10^{-13}$)	$1.9078*10^{-14}$ ($4.11*10^{-13}$)	$5.32*10^{-13}$ ($3.51*10^{-13}$)
Std(labor)	-0.0776 (0.0217)	-0.1097 (0.0205)	-0.1665 (0.0190)
Cov(Δlnw_{it}, R_t)	-0.0180 (0.0059)	-0.0185 (0.0057)	-0.0190 (0.0053)
If the head is male	0.3327 (0.0600)	0.3358 (0.0565)	0.4266 (0.0592)
If the head is in financial firm	0.1595 (0.0848)	0.3381 (0.0787)	0.2201 (0.0788)
If the head is in other services	0.2371 (0.0512)	0.2005 (0.0518)	0.1873 (0.0522)
Age of head	0.0119 (0.0019)	0.0131 (0.0019)	0.0144 (0.0017)
If the head has college or above degree	0.5243 (0.0508)	0.6822 (0.0485)	0.4719 (0.0446)
If the head has a management or professional job	0.4564 (0.0517)	0.3298 (0.0506)	0.5434 (0.0465)
Number of children of the head in 1984	-0.0002 (0.0027)	-0.0080 (0.0030)	-0.0068 (0.0027)
Race of the head	0.7437 (0.0584)	0.7909 (0.0567)	0.7149 (0.0563)
Brokers per capita	0.0348 (0.0199)	0.0088 (0.0169)	0.0547 (0.0143)
Per capita income	0.00002 (0.00001)	$-1.2543*10^{-6}$ ($8.976*10^{-6}$)	$5.1793*10^{-7}$ ($8.015*10^{-6}$)

Table 15. Testing the Effect of Brokers per capita by Adding Per Capita Income (Probit Step)

	1984	1989	1994
intercept	-465724 (209032)	-594533 (251735)	-587245 (399953)
E(labor)	$-2.668*10^{-8}$ $(0.012*10^{-5})$	$0.0014*10^{-3}$ $(0.032*10^{-4})$	$4.31*10^{-8}$ $(0.007*10^{-5})$
Std(labor)	-4883 (4609)	-17577 (8854)	-26403 (23449)
Cov(Δlnw_{it}, R_t)	-1524 (1073)	-3183 (1717)	-7031 (3444)
If the head is male	51505 (18857)	56313 (26155)	70561 (27234)
If the head is in financial firms	24557 (10044)	52713 (24812)	29834 (23614)
If the head is in other services	26213 (12416)	47109 (16622)	22516 (10020)
Age of head	2293 (637)	3836 (929)	5327 (1913)
If head has college or above degree	71083 (27720)	107902 (47792)	59177 (59166)
If head has management or professional job	51748 (24120)	48090 (23720)	80021 (36481)
If the head is white	87337 (42392)	110916 (59652)	88639 (43048)
Brokers per capita (1 out of 1000 population)	3068 (2265)	4334 (3550)	12615 (8004)
Per capita income	1.5227 (1.3157)	1.9950 (1.7903)	-1.3046 (3.0288)
Inverse mill's ratio	146916 (73255)	167865 (96779)	190870 (183375)

Table 16. Testing the Effect of Brokers per capita by Adding Per Capita Income (Sample Selection Step)

1989 \ 1984	0	1	2	3	4
0	0.6677	0.0399	0.0326	0.0276	0.0133
1	0.0248	0.0147	0.0102	0.0029	0.0018
2	0.0209	0.0086	0.0080	0.0100	0.0066
3	0.0164	0.0035	0.0096	0.0127	0.0141
4	0.0084	0.0023	0.0035	0.0078	0.0321
total	0.7381	0.069	0.0639	0.0610	0.0680

Table 17. Transition Matrix of 1984-1989

Note: State 0: no stock

Then the remaining sample is equally divided into 4 subgroups, with the amount of stock holding increasing in each group.

1989 \ 1984	0	1	2	3	4
0	0.9046	0.5783	0.5102	0.4525	0.1956
1	0.0336	0.2130	0.1596	0.0475	0.0265
2	0.0283	0.1246	0.1252	0.1639	0.0970
3	0.0222	0.0507	0.1502	0.2082	0.2074
4	0.0114	0.0333	0.0548	0.1279	0.4721

Table 18. Probability Matrix 1984-1989

1994 \ 1989	0	1	2	3	4
0	0.6183	0.0415	0.0355	0.0287	0.0142
1	0.0314	0.0150	0.0099	0.009	0.0039
2	0.0193	0.0115	0.0111	0.0133	0.0088
3	0.0133	0.0047	0.0140	0.0150	0.0133
4	0.0131	0.0021	0.0068	0.0103	0.0359
total	0.6955	0.0747	0.0772	0.0764	0.0762

Table 19. Transition Matrix 1989-1994

1994 \ 1989	0	1	2	3	4
0	0.8890	0.5556	0.4598	0.3757	0.1864
1	0.0451	0.2008	0.1282	0.1178	0.0512
2	0.0277	0.1539	0.1438	0.1741	0.1155
3	0.0191	0.0629	0.1813	0.1963	0.1745
4	0.0188	0.0281	0.0881	0.1348	0.4711

Table 20. Probability Matrix 1989-1994

1994 \ 1984	0	1	2	3	4
0	0.6253	0.0480	0.0437	0.0392	0.0246
1	0.0263	0.0107	0.0099	0.0051	0.0027
2	0.0179	0.0066	0.0074	0.0121	0.0103
3	0.0140	0.0066	0.0094	0.0140	0.0125
4	0.0121	0.0029	0.0068	0.0060	0.0261
total	0.6955	0.0747	0.0772	0.0764	0.0762

Table 21. Transition Matrix 1984-1994

1994 \ 1984	0	1	2	3	4
0	0.8991	0.6426	0.5661	0.5131	0.3228
1	0.0378	0.1432	0.1282	0.0668	0.0354
2	0.0257	0.0884	0.0959	0.1584	0.1352
3	0.0201	0.0884	0.1218	0.1832	0.1640
4	0.0174	0.0388	0.0881	0.0785	0.3425

Table 22. Probability Matrix 1984-1994

1984 \ 1989	In the market	Out of the market	Total
In the market	733	338	1071
Out of the market	559	3254	3813
Total	1292	3592	4884

Table 23. Entering/Quiting Equity Market 1984-1989

1994 \ 1989	In the market	Out of the market	Total
In the market	916	372	1288
Out of the market	585	2997	3582
Total	1501	3369	4870

Table 24. Entering/Quiting Equity Market 1989-1994 (14 non-response)

	1984	**1989**	**1994**
intercept	-2.4292 (0.1129)	-2.4088 (0.1205)	-1.8055 (0.1128)
E(labor income)	$-3.202*10^{-14}$ $(4.37*10^{-13})$	$1.8230*10^{-14}$ $(3.82*10^{-13})$	$5.6173*10^{-13}$ $(4.18*10^{-13})$
Std(labor income)	-0.0851 (0.0217)	-0.1209 (0.0205)	-0.1775 (0.0191)
$Cov(\Delta lnw_{it}, R_{it})$	-0.0110 (0.0059)	-0.0091 (0.0029)	-0.0075 (0.0025)
CovWH	$-2.1958*10^{-7}$ $(0.7219*10^{-7})$	$-3.4968*10^{-7}$ $(0.7391*10^{-7})$	$-4.6359*10^{-7}$ $(0.7225*10^{-7})$
If the head is male	0.3297 (0.0598)	0.3199 (0.0565)	0.3965 (0.0498)
If the head is in financial firm	0.1601 (0.0846)	0.3446 (0.0783)	0.1887 (0.0773)
If the head is in other service	0.2135 (0.0509)	0.1971 (0.0517)	0.1843 (0.0519)
Age of head	0.0110 (0.0019)	0.0114 (0.0019)	0.0129 (0.0017)
If the head has college or above degree	0.5092 (0.0506)	0.6732 (0.0484)	0.4642 (0.0445)
If the head has managerial or professional job	0.4541 (0.0514)	0.3337 (0.0504)	0.5034 (0.0462)
If the head is white	0.7141 (0.0576)	0.7772 (0.0564)	0.6580 (0.0508)
Broker per Capita	0.0349 (0.0187)	0.0088 (0.0170)	0.0540 (0.0135)

Table 25. Probit Model with the Covariance of Labor Income and House Value

	1984	1989	1994
intercept	-397671 (187562)	-544483 (253043)	-636947 (389726)
E(labor income)	$-2.1658*10^{-8}$ $(1.2*10^{-7})$	$1.488*10^{-6}$ $(3.1*10^{-7})$	$4.4316*10^{-8}$ $(7.0*10^{-8})$
Std(labor income)	-5260 (4887)	-18636 (9251)	-32242 (25177)
$Cov(\Delta lnw_{it}, R_{it})$	-1218 (979)	-2935 (1767)	-5041 (3413)
CovWH	-0.0119 (0.0056)	-0.0173 (0.0082)	-0.0482 (0.0229)
If the head is male	47734 (18745)	53535 (26085)	68529 (27146)
If the head is in financial firm	22990 (9792)	49597 (24741)	30084 (30761)
If the head is in other service	22048 (11324)	44059 (16530)	21568 (10025)
Age of head	2292 (667)	4032 (976)	5465 (1921)
If the head has college or above degree	63686 (26628)	10204 (48254)	59844 (57100)
If the head is white	74746 (40091)	105030 (59905)	82301 (41003)
Broker per Capita	2639 (2054)	3849 (3391)	12584 (7663)
Inverse mills ratio	129468 (71026)	179015 (97381)	198463 (179764)

Table 26. Sample Selection Model with the Covariance of Labor Income and House Value

	1984	1989	1994
intercept	-2.4314 (0.1130)	-2.4193 (0.1207)	-1.8174 (0.1123)
E(labor income)	$-3.112*10^{-14}$ ($4.03*10^{-13}$)	$-1.275*10^{-14}$ ($1.08*10^{-13}$)	$4.4106*10^{-13}$ ($2.59*10^{-13}$)
Std(labor income)	-0.0848 (0.0217)	-0.1208 (0.0207)	-0.1766 (0.0190)
Cov(Δlnw_{it}, R_{it})	-0.0112 (0.0041)	-0.0121 (0.0059)	-0.0137 (0.0055)
CovWH	$-2.3798*10^{-7}$ ($0.7219*10^{-7}$)	$-3.4972*10^{-7}$ ($0.7398*10^{-7}$)	$-4.7804*10^{-7}$ ($0.7227*10^{-7}$)
CovSH	-0.0035 (0.0006)	-0.0117 (0.0046)	-0.0121 (0.0045)
If the head is male	0.3312 (0.0599)	0.3241 (0.0566)	0.4138 (0.0598)
If the head is in financial firm	0.1595 (0.0746)	0.3442 (0.0783)	0.1883 (0.0773)
If the head is in other service	0.2139 (0.0509)	0.1985 (0.0517)	0.1868 (0.0520)
Age of head	0.0111 (0.0019)	0.0117 (0.0019)	0.0132 (0.0018)
If the head has college or above degree	0.5091 (0.0506)	0.6727 (0.0485)	0.4518 (0.0445)
If the head has managerial or professional job	0.4538 (0.0514)	0.3345 (0.0504)	0.5036 (0.0463)
If the head is white	0.7130 (0.0576)	0.7740 (0.0565)	0.7115 (0.0509)
Broker per Capita	0.0347 (0.0186)	0.0076 (0.0164)	0.0562 (0.0137)

Table 27. Probit Model with the Covariance of Stock Return and House Return

	1984	1989	1994
intercept	9273 (20546)	-82504 (56812)	-506164 (153504)
E(labor income)	$-2.2443*10^{-8}$ $(1.1521*10^{-7})$	$1.31*10^{-8}$ $(3.133*10^{-7})$	$3.3598*10^{-8}$ $(5.0*10^{-8})$
Std(labor income)	5053 (4811)	-15454 (9219)	-31628 (21129)
Cov(Δlnw_{it}, R_{it})	-1230 (979)	-2729 (1769)	-5057 (3426)
CovWH	-0.0135 (0.0057)	-0.0171 (0.0082)	-0.0476 (0.0219)
CovSH	-0.0527 (0.0139)	-0.0631 (0.0104)	-0.0738 (0.0165)
If the head is male	47730 (18710)	53839 (25800)	68502 (27162)
If the head is in financial firm	22112 (9883)	49491 (24479)	31362 (30742)
If the head is in other service	23979 (11398)	44543 (16372)	22190 (10074)
Age of head	2302 (669)	4121 (1001)	5445 (1886)
If the head has college or above degree	64060 (26710)	14048 (44896)	59916 (54230)
If the head is white	74437 (40036)	105409 (53772)	82931 (39513)
Broker per Capita	2624 (2038)	3914 (3400)	12679 (7673)
Inverse mills ratio	133263 (20639)	152476 (58041)	169495 (75639)

Table 28. Sample Selection Model with the Covariance of Stock Return and House Value

	1984	1989	1994
Home owners	7857	15123	35836
Non home owners	870	1869	5352

Table 29. The Mean Value of Stock Holding for Homeowners and Non Homeowners

	Count	Percentage
Ever BK	526	6.33%
Never BK	7781	93.67%
Total	8307	100%

Table 30. Ever Bankruptcy Distribution in 1996 PSID Core Family Survey

	Count	Percentage
Ever delinquent	2086	25.11%
Never delinquent	6221	74.89%
Total	8307	100%

Table 31. Ever Default Distribution in 1996 PSID Core Family Survey

	Mean
Age of household head	44
If household head is male	0.69
If household head is married	0.52
If household head is college-educated	0.21
If household head is Caucasian	0.56
Number of kids	0.91
If household head is unemployed	0.33

Table 32. Mean Values of Independent Variables in the Regression

	Estimate	Standard Error
State unemployment rate	0.1260	0.0086
If head is college-educated	-0.3909	0.0403
Age of head	0.0221	0.0009
If head is male	-0.3245	0.0407
If head is married	-0.4526	0.0417
If head is white	-0.2893	0.0318
Number of kids	-0.0610	0.0131

Table 33. Bivariate Probit Regression: Unemployment Equation

	Estimate	Standard Error
If head was unemployed	1.4207	0.1156
Family income ($00,000)	-0.1550	0.0467
State property exemption ($0,000)	0.1802	0.0284
If head is college-educated	-0.4677	0.0532
Age of head	-0.1541	0.0023
If head is male	-0.3354	0.0537
If head is married	-0.0693	0.0606
If head is white	-0.1838	0.0389
Number of kids	0.0401	0.0152

Disturbance Correlation: Rho(1, 2)=0.7238

Table 34. Bivariate Probit Model: Bankruptcy Filing Equation

	Estimate	Standard Error
If head was unemployed	0.7127	0.1151
Family income ($0,000)	-0.1928	0.0031
If head is college-educated	-0.0046	0.0411
Age of head	-0.2595	0.0014
If head is male	-0.1373	0.0403
If head is married	-0.1616	0.0434
If head is white	-0.1021	0.0309
Number of kids	0.0986	0.0136

Disturbance Correlation: Rho(1, 2)=0.1683

Table 35. Bivariate Probit Model: Bill Delinquency Equation

	Count	Percentage
Chapter 7	264	50.29%
Chapter 13	261	49.71%
Total	525	100%

Table 36. Chapter of Bankruptcy Filing

	Estimate	Standard Error
Age of household head	0.0088	0.0050
Debt/wealth ratio	-0.0010	0.0003
If head was unemployed	-0.4204	0.1721
Inverse Mills ratio	-0.6802	0.3097

* wealth is approximated by house value plus family income.

Table 37. Probit Analysis of Filing for Chapter 13 Bankruptcy

APPENDIX B

The Panel Study of Income Dynamics (PSID) is a longitudinal survey data conducted by the University of Michigan since 1968. Over its life, it has been funded by several government agencies, foundations and organizations. Their current major funding sources are the National Science Foundation and the National Institute on Aging.

The PSID data is a panel study of representative U.S. individuals (men, women and children) and the household they reside in. Its emphasis is the dynamic aspects of economic and demographic behavior. But the actual coverage is much broader than these. In the recent years, special topics include extensive questionnaire on wealth and credit background, which has been very useful for the purpose of this dissertation.

The survey project has been very successful in re-interviewing families previously in the study and following new families as young adults "split off" from their parents. The sample households included in the study is about 7000 now. Previous research has shown that PSID is a good source of information on the distribution of basic economic variables such as income, wealth, homeownership and employment in the larger population. One of the important features of PSID data is its comparability of data quality and structure over time. The general design and content of certain important income and demographic variables have remained unchanged, which makes it easy to construct a clean and consistent time series of income dynamics for each individual or household.

This paper is a study on the preference of general household investment, it is important to have a data set representative of American households. PSID is the only longitudinal representation of families and individuals of all ages. National Longitudinal Survey (NLS) and Health and Retirement Study (HRS) also provide data of panel features. However, the samples are tilted toward either young cohort or older cohort, who have represented different investment behavior as pointed out in the literature.

As one of the most important measures in this paper is labor income risk over the 15 year period, PSID provides the best estimation. Income measures in PSID include taxable income, transfer income, social security, asset income, and business income. And the measures are mostly available for head, "wife" and other family members. Each wave's report also has the 3-digit Census code on the head's and wife's occupation and industry.

Gouskova and Schoeni (2002) compared the annual income observations from PSID with March Current Population Survey, which is a cross-sectional national survey, and is the basis for the government's official estimates of income and poverty. They compared income estimates for the PSID history 1968-1999. The results show that the distributions match closely in the range between the 5^{th} and 95^{th} percentile through the entire 30-year history of PSID. And the differences slowly disappeared during the 1980s and early 1990s. As this dissertation uses data PSID data from 1980s to early 1990s, we should thus be able to infer that the income risk measures in this paper are representative of U.S. household.

The active savings file and the wealth supplements provide rich sources on flow of money in and out of different assets. Curtin, Juster and Morgan (1988) examined the quality of PSID wealth data and found it representative of total wealth and the distribution of wealth in the great bulk of the U.S. population. They also found the overall potential of examining wealth using PSID data is comparable to using Survey of Consumer Finance data on a cross-sectional basis. However, we did not use SCF data due to the fact that it does not provide the unique panel feature essential for measuring income risk. The general descriptive statistics from PSID are also closer to the actual population than that provided by SIPP. The PSID data also has a much lower non-response rate than SIPP, and is much less necessary to impute certain values, which reduces potential estimation error.

The 1996 wave of core family data in PSID also provides questions on bill payment delinquency and bankruptcy filings, which enabled the study of the third essay in this dissertation. This feature will be otherwise unavailable in the other panel data sets.

For the sample used in the first and second essays in this dissertation, I use data from 1979-1996. I drop the Latino over-sample in 1990-1992. I then use 1979 as my base year, treating all families in this year as main families, and subsequent split off families are dropped from the sample. A family is also dropped if it did not respond in any year. Finally, I drop the two cases in which total asset income of other family members is top-coded. This leaves a balanced panel of 4884 households.

Table 2 shows the sample selection criteria for the first two essays. Table 3 shows the variables used in the regressions and their mean values. The mean family labor income in 1994 from my sample is about $42,000. And the mean family total income from PSID 1994 total sample is about $47,000. We can see that the level of labor income after my sample selection remains comparable and representative as in the original PSID sample.

Table 6 shows that the percentage of stock ownership ranges from 20% to 30% in the sample periods, which is also comparable to the literature during the same time span.

Overall, the important input variables for this dissertation include family demographics, labor income dynamics, the self-reported house value, the amount of stock ownership and the value of checking and savings account. Careful examination of each of the component shows that they are comparable to other major household survey data on a cross-sectional basis, representative of the general households and could provide panel features as well, which won't be available other wise. In no ways, this data set could be perfect. However, we are trying to use the best information possible and the available resources from PSID are rich enough for us to examine income risk profiles and household stock participation preferences on a panel basis.

LIST OF REFERENCES

Abel, B.A. (2000) "The effects of investing Social Security funds in the stock market when fixed costs prevent some households from holding stocks."

Agarwal, S., Liu, C., and Mielnicki, L. (2003) "Exemption laws and consumer delinquency and bankruptcy behavior: An empirical analysis of credit card data." *The Quarterly Review of Economics and Finance* 43, 273-289.

Agnew, J., Balduzzi, P. and Sunden, A. (2000) "Portfolio choice, trading, and returns in a large 401(K) plan." Working paper, Center for Retirement Research at Boston College.

Altman, E. (1968) "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy." *Journal of Finance* 20, 589-609.

Altman, E. and Saunders, A. (1997) "Credit risk measurement: Developments over the last 20 years." *Journal of Banking and Finance* 21 (11-12), 1721-1742.

Angerer, W. Xiaohong (2003) "Income Risk and Portfolio Choice: An Empirical Study." Department of Economics, The Ohio State University, Ph.D. Defense (2004)

Bangia, A., Diebold, F. and Schuermann, T. (2000) "Rating migration and the business cycle, with application to credit portfolio stress testing" PIER working paper No. 01-004.

Bernanker, B.S. and Blinder, A.S. (1988) "Is it money or credit, or both, or neither?" *American Economic Review Papers Proc*. 78, 435-439.

Bernanker, B.S. and Gertler, M. (1995) "Inside the black box: The credit channel of monetary policy transmission." *Journal of Economic Perspectives* 9, 27-48.

Bertaut, C. and Starr-McCluer, M. (2000) "Household portfolios in the United States." Federal Reserve Board of Governors.

Bernheim, B. and Garrett, M. "The determinants and consequences of financial education in the workplace: Evidence from a survey of households."

Bester, H. (1985) "Screening vs. rationing in credit markets with imperfect information" *American Economic Review* LXXV, 850-855.

Boot, A., and Udell, G. (1991) "Secured Lending and Default Risk: Equilibrium Analysis, Policy Implication and Empirical Results." *The Economic Journal* CI, 458-472.

Boyes, W., Hoffman, D. and Low, S. (1989) "An econometric analysis of the bank credit Scoring Problem." *Journal of Econometrics* XL, 3-14.

Brueckner, K. J. (1997) "Consumption and investment motives and the portfolio choices of homeowners." *Journal of Real Estate Finance and Economics* 15(2), 159-180.

Carey, M. (1998) "Credit risk in private debt portfolios." *Journal of Finance* 53(4), 1363-1387.

Carey, M. (2002) "A guide to choosing absolute bank capital requirements." FRB International Finance Discussion Paper No.726.

Chakraborty, A. and Kazarosian, M. (1999) "Portfolio allocation of precautionary assets: Panel Evidence for the United States."

Cocco, F. (2000) "Portfolio choice in the presence of housing.", London Business School.

Cox, D. and Jappelli, T. (1993) "The effect of borrowing constraints on consumer liabilities." *Journal of Money, Credit and Banking* XXV, 197-213.

Crouchy, M., Galai, D. and Mark, R. (2000) "A comparative analysis of current risk Models." *Journal of Banking and Finance* 24(1-2), 59-117.

Domowitx, I. and Sartain, R. (1999) "Determinants of the consumer bankruptcy decision." *The Journal of Finance* 54(1), 403-420.

Duffee, G. (1999) "estimating the price of default risk." *Review of Financial Studies* 12(1), 197-226.

Ervin, W. and Wilde, T. (2004) "Pro-cyclically in the new Basel Accord." Risk

Fay, S., Hurst, E. and White, M. (1998) "The bankruptcy decision: does stigma matter?" Working paper, University of Michigan.

Flavin, M. and Yamashita, T. (1998) "Owner-occupied housing and the composition of the household portfolio over the Life Cycle." NBER Working Paper No. 6389, forthcoming *American Economic Review*.

Gakidis, E. (1998) "Portfolio choice and uninsurable labor earnings." Ph.D dissertation, MIT.

Giesecke, K. (2004) "Successive correlated defaults in a structural model." SSRN Working Paper No. 551024.

Goetzmann, N.W. (1993) "The single family home in the investment portfolio." *Journal of Real Estate Finance and Economics* 1, 201-222.

Goetzmann, N.W. and Ibbotson, G.R. (1990) "The performance of real estate as an asset Class." *Journal of Applied Corporate Finance*

Green, H.W. *Econometric Analysis*. 3rd ed.

Gropp, R and Scholz, J. (1996) "Personal bankruptcy and credit supply and demand." NBER Working Paper No. 5653.

Gross, D. and Souleles, N. (2001) "Do liquidity constraints and interest rate matter for consumer behavior? Evidence from credit card data." forthcoming in *The Quarterly Journal of Economics*.

Gouskova, E. and Schoeni, R. (2002) "Comparing Estimates of Family Income in the Panel Study of Income Dynamics and the March Current Population Survey, 1968-1999." PSID website

Guiso, L., Jappelli, T. and Terlizzese, D. (1996) "Income risk, borrowing constraints, and Portfolio Choice." *The American Economic Review* 86(1), 158-172.

Guiso, L., Sapienza, P. and Zingales, L. (2002) "Does Local Financial Development Matter?" NBER Working Paper No. 8923.

Heaton, J. and Lucas, D. (2000) "Portfolio Choice in the Presence of Background Risk." *The Economic Journal* 110, 1-26.

Heaton, J. and Lucas, D. (2000) "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk." *The Journal of Finance* LV(3), 1163-1197.

Heckman, J. (1979) "Sample Selection Bias as a Specification Error." *Econometrica* 47, 1), 153-162.

Henderson, J.V. and Ioannides, Y.M (1993) "A Model of Housing Tenure Choice." *The American Economic Review* 73(1), 98-113.

Hubbard, R.G., Skinner, J., and Zeldes, P. (1995) "Precautionary Saving and Social Insurance." *Journal of Political Economy* 103(2), 360-399.

Hurst, E., Luoh, M. and Stafford, P.F. (1998) "The Wealth Dynamics of American Families, 1984-94." *Brookings Papers on Economic Activities* 1, 267-337.

Jappelli, T. (1990) "Who is Credit Constrained in the US Economy?" *Quarterly Journal of Economics* CV, 219-234.

Kennickell, B.A. and Starr-McCluer, M. (1996) "Household Saving and Portfolio Change: Evidence from the 1983-89 SCF Panel." Federal Reserve Board of Governors.

Kim, Y. and Stafford, F. (2000) "The Quality of PSID Income Data in the 1990's and Beyond." PSID website

Kimball, S.M. (1993) "Standard Risk Aversion" *Econometrica* 61(3), 589-611.

Koopman, G., Lucas, A. and Klaassen, P. (2003) "Pro-Cyclicality, Empirical Credit Cycles, and Capital Buffer Formation" EFA 2003 Annual Conference Paper No. 211.

Lang, W. and Santomero, A. "Risk quantification of retail credit: Current practice and future challenges." Federal Reserve Bank of Philadelphia.

Lawrence, E. (1995) "Consumer Default and the Life Cycle Model" *Journal of Money, Credit and Banking* 27(4, Part I), 939-954.

Li, W. (2001) "To Forgive or Not to Forgive: An Analysis of U.S. Consumer Bankruptcy Choices." *Economic Quarterly, Federal Reserve Bank of Richmond* 87(2),

Li, W. and Sarte, P. (2002) "The Macroeconomics of U.S. Consumer Bankruptcy Choice: Chapter 7 or Chapter 13?" Federal Reserve Bank of Richmond Working Paper 02-01.

Livshits, I. and MacGee, J. (2001) "Consumer Bankruptcy: A Fresh Start." Federal Reserve Bank of Minneapolis Working Paper 617.

Lopez, J. and Saidenberg, M. (2000) "Evaluating Credit Risk Models." *Journal of Banking and Finance* 24(1/2), 151-167.

Mays, E. (2004) "Credit Scoring for Risk managers" South-Western.

Mella-Barral, P. and Perraudin, W. (1997) "Strategic Debt Service." *Journal of Finance* 52(2), 531-556.

Myers, H. and Forgy, W. (1963) "The Development of Numerical Credit Evaluation System." *Journal of the American Statistics Association* 58, 799-806.

Pesaran, H., Schuermann, T. Treutler, B-J., and Weiner, S. (2003) "Macroeconomic dynamics and credit risk: A global perspective."

Poterba, M.J. (2001) " The Rise of the 'Equity Culture': U.S. Stockownership Patterns, 1989-1998." Working paper,

Rampini, A. (2004) "Default and Aggregate Income." Ph.D. dissertation, Department of Finance, Northwestern University.

Santos, T. and Veronesi, P. (2001) “Labor Income and Predictable Stock Returns.” Working paper, University of Chicago, NBER and CEPR.

Sims, C. (1980) “Macroeconomics and Reality.” *Econometrica* 48, 1-48.

Souleles, S.N. (2001) “Household Portfolio Choice, Transaction Costs, and Hedging Motives.” Working paper, Finance Department, University of Pennsylvania and NBER.

Sullivan, C. (1987) “Economic Factors Associated with Delinquency Rates on Consumer Installment Debt” Working Paper 55, Credit Research Center, Krannert Graduate School of Management, Purdue University.

The Panel Study of Income Dynamics: A User’s Guide, volume 2, 1991, http://psidonline.isr.umich.edu/Guide/ug/tablcont.html

Thomas, L.C., Edelman, D.B. and Crook, N.J. (2002) “Credit Scoring and its applications.” Society for Industrial and Applied Mathematics.

Viceira, M.L. (2001) “Optimal Portfolio Choice for Long-Horizon Investors with Nontradable Labor Income.” *Journal of Finance*

Vissing-J∅rgensen, A. (2000) “Towards an explanation of household portfolio choice heterogeneity: Nonfinaicial income and participation cost structures.” Working paper, Department of Economics, University of Chicago.

Wang, H. and White, M. (2000) “An optimal personal bankruptcy procedure and proposed reforms.” *Journal of Legal Studies* 29(1), 255-286.

Whitford, W. (1989) “Has the time come to repeal Chapter 13?” *Indiana Law Journal* 65, 85-105.

Yao, R. and Zhang, H. (2002) “Optimal Consumption and Portfolio Choices with Risky Housing and Stochastic labor Income.” Working paper, Kenan-Flagler Business School, The University of North Carolina at Chapel Hill.

Zywicki, T. (2002) “The economics of credit cards.” Working paper, George Mason University.